Language Technologies Institute

Carnegie Mellon University

Multimodal Machine Learning

Lecture 3.1: CNNs and Visual Representations

Louis-Philippe Morency

* Original version co-developed with Tadas Baltrusaitis

Administrative Stuff

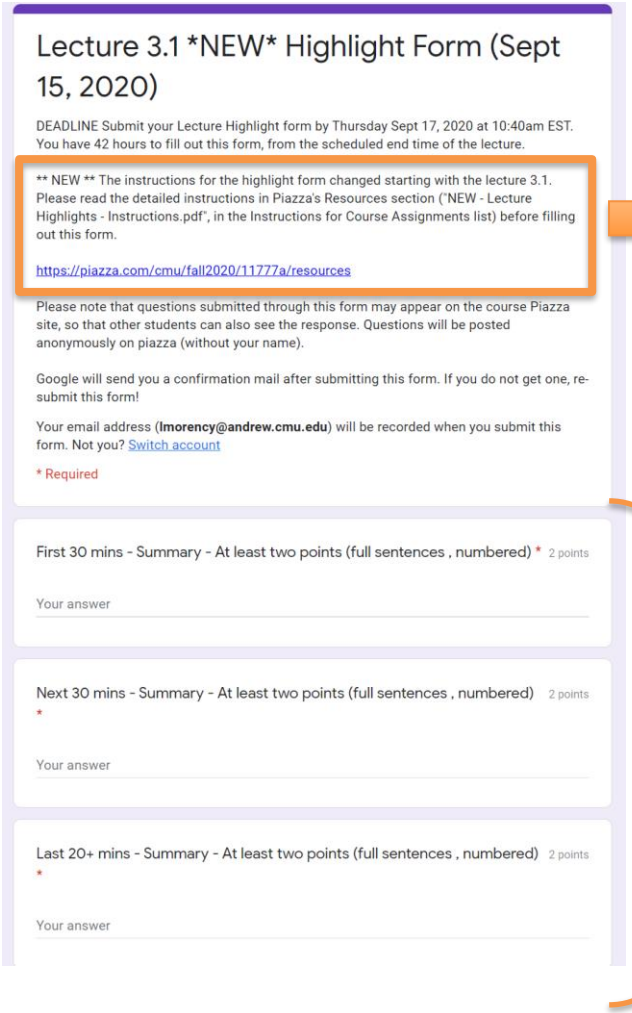
Pre-proposals – Due tomorrow 9/16

- Dataset and research problem
- Input modalities and multimodal challenges
- Initial research ideas
- Teammates and resources

Submit via Gradescope before 8PM ET

If you are still looking for teammates, you should still submit a pre-proposals. We will help you!

NEW Lecture Highlight Forms



Lecture 3.1 *NEW* Highlight Form (Sept 15, 2020)

DEADLINE Submit your Lecture Highlight form by Thursday Sept 17, 2020 at 10:40am EST. You have 42 hours to fill out this form, from the scheduled end time of the lecture.

** NEW ** The instructions for the highlight form changed starting with the lecture 3.1. Please read the detailed instructions in Piazza's Resources section ("NEW - Lecture Highlights - Instructions.pdf", in the Instructions for Course Assignments list) before filling out this form.

https://piazza.com/cmu/fall2020/11777a/resources

Please note that questions submitted through this form may appear on the course Piazza site, so that other students can also see the response. Questions will be posted anonymously on piazza (without your name).

Google will send you a confirmation mail after submitting this form. If you do not get one, re-submit this form!

Your email address (**lmorency@andrew.cmu.edu**) will be recorded when you submit this form. Not you? Switch account

* Required

First 30 mins - Summary - At least two points (full sentences , numbered) * 2 points

Your answer

Next 30 mins - Summary - At least two points (full sentences , numbered) 2 points *

Your answer

Last 20+ mins - Summary - At least two points (full sentences , numbered) 2 points *

Your answer

https://forms.gle/ihEu5JVxFCmrCEEi7

New set of instructions…

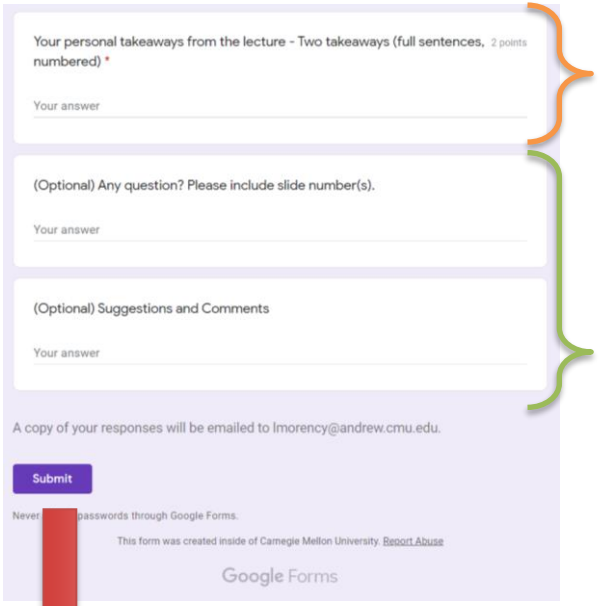
…but same deadline: **Thursday 10:40am**

Step 1: Write for each segment at least 2 main discussed points

- Write complete sentence (10+ words)
- Number your main points: (1), (2), …
- Do not be vague or simply list keywords

NEW Lecture Highlight Forms

https://forms.gle/ihEu5JVxFCmrCEEi7



Step 2: Write your 2 personal takeaways from the whole lecture

- Write complete sentence (10+ words)
- Number your main points: (1), (2), …
- Make it personal ("I liked…", "I was surprised…")

Two optional fields:

1. Any question about the lecture?
2. Any other suggestions?
   - This could help us with next edition of the course

IMPORTANT: Be sure you received an email after your submission

Upcoming Deadlines

Week 3 reading assignment was posted

1. **Wednesday 8pm:** Select your paper
2. **Friday 8pm:** Post your summary
3. **Monday 8pm:** End of the reading assignment

Preproposal deadline: **Wednesday 8pm**

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Multimodal Machine Learning

Lecture 3.1: CNNs and Visual Representations

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Lecture Objectives

- Image representations
  - Object descriptors
- Convolutional Neural networks
  - Convolution kernels
  - Convolution neural layers
  - Pooling layers
- Convolutional architectures
  - VGGNet and residual networks
  - Visualizing CNNs
  - Region-based CNNs
  - Sequential Modeling with convolutional networks
- Appendix: Tools for visual behavior analysis

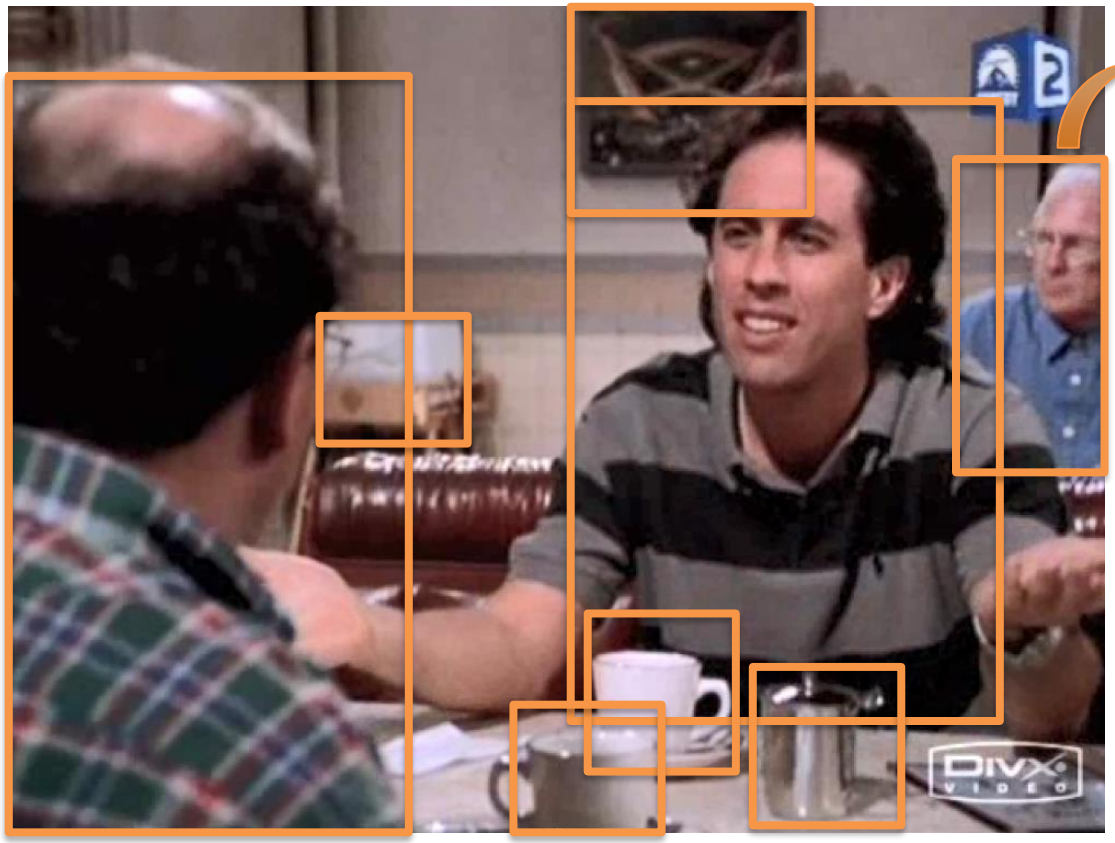
Image Representations

How Would You Describe This Image?

?

88
88
85
38
20
22
24
21
23
82
80
79
35
25
26
28
22
22
84
78
80
⋮

Object-Based Visual Representation



“person” label

+

Appearance descriptor

- ❑ Age
- ❑ Expression
- ❑ Clothes
- ❑ …

Feature vector

88
88
85
38
20
22
24
21
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82
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84
78
80

Object Descriptors

How to represent and detect an object?

Many approaches over the years…

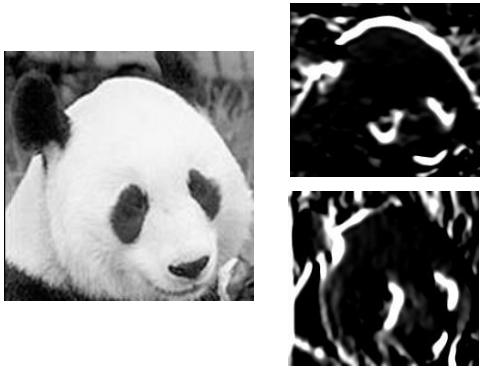
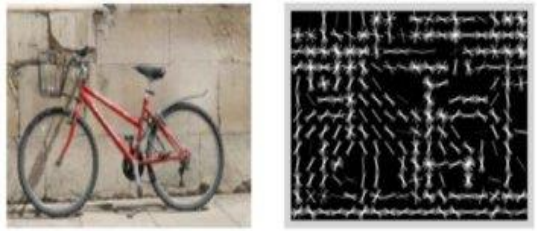


Image gradient

Edge detection



Histograms of Oriented Gradients

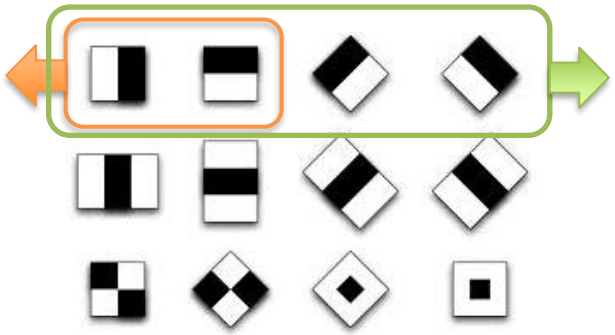
Optical Flow

Object Descriptors

How to represent and detect an object?

Many approaches over the years…

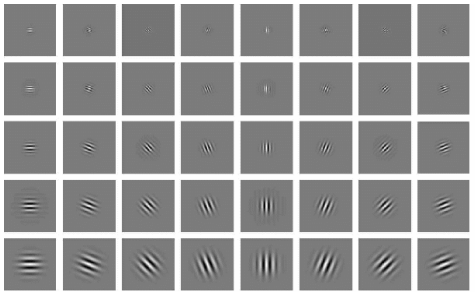
Horizontal and vertical gradients



Oriented gradients

Haar Wavelets

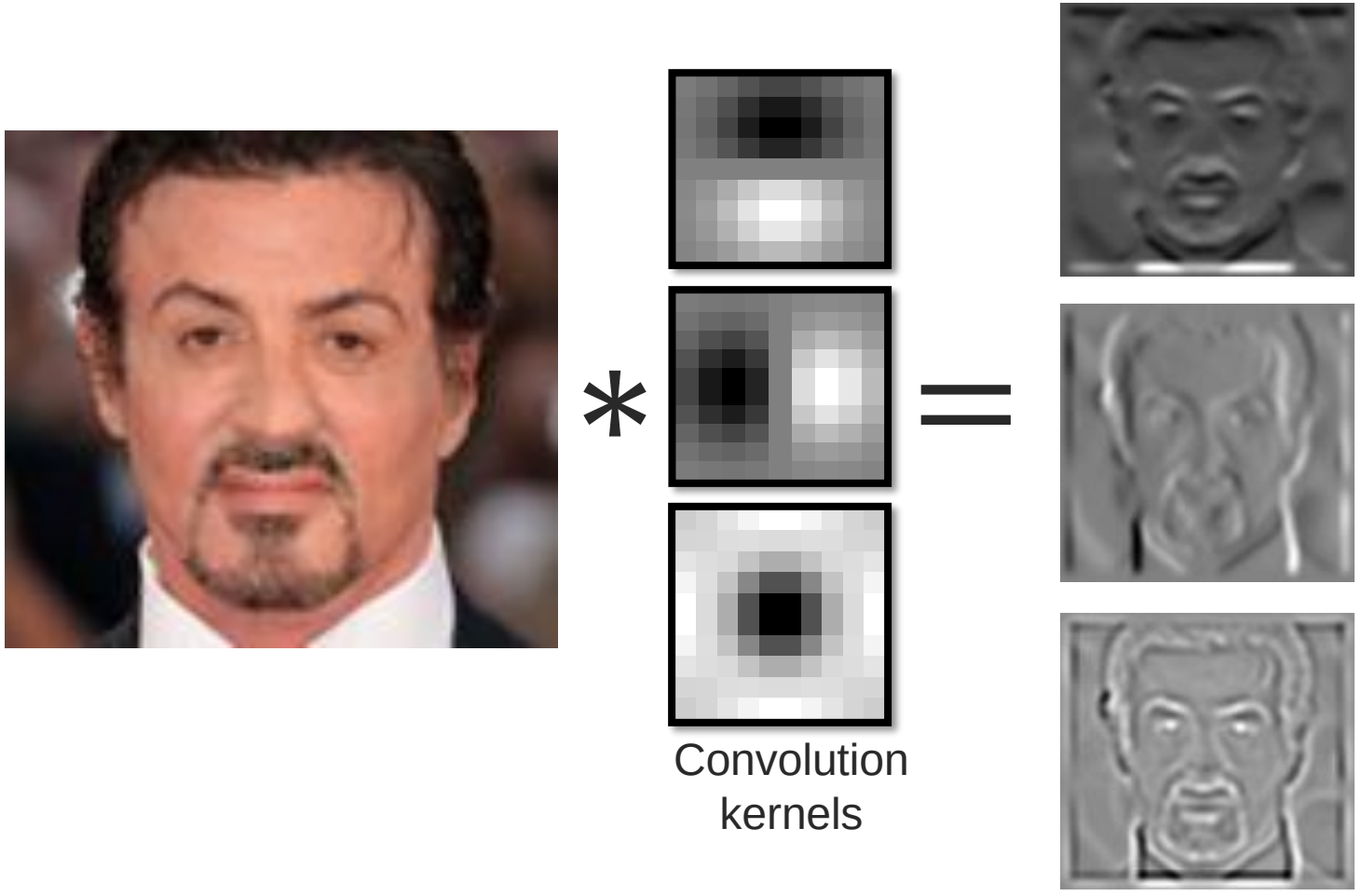
Templates tested on the image *(i.e., convolution kernels)*



Gabor filters

Inspired by visual cortex

Convolution Kernels

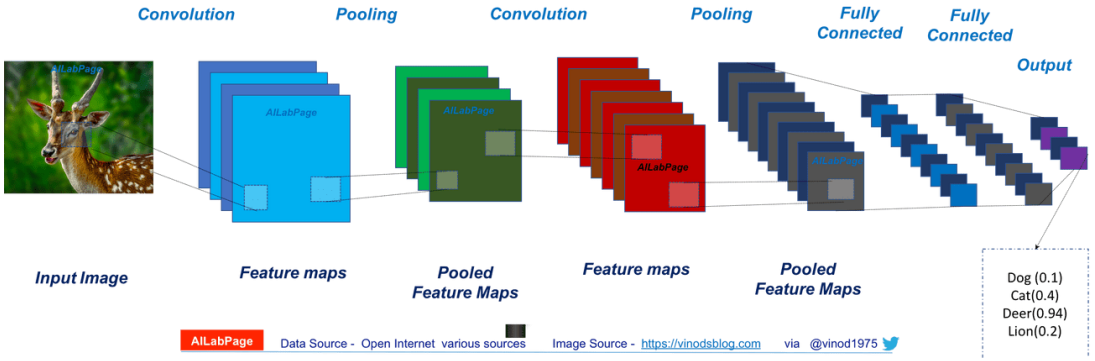


Object Descriptors

How to represent and detect an object?

Many approaches over the years…

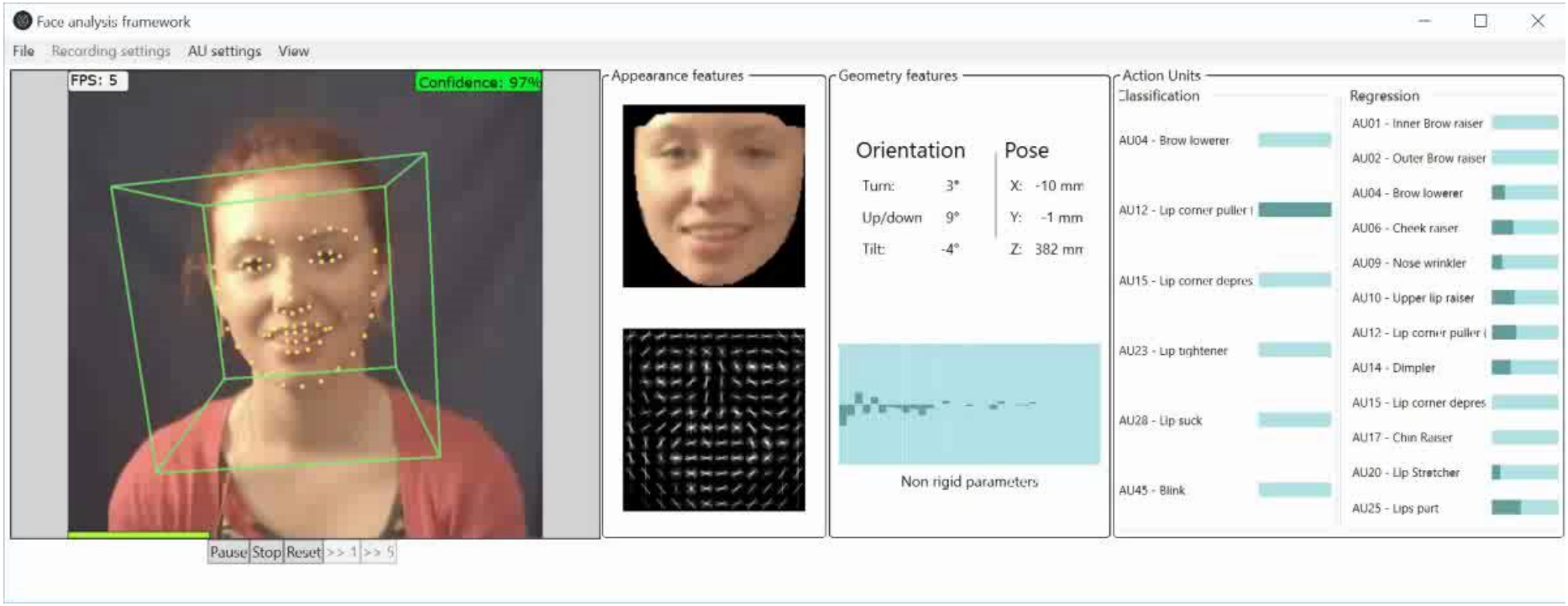
Convolutional Neural Network (CNN)



More details about CNNs is coming…

And images are more than a list of objects!

Facial expression analysis



[**OpenFace: an open source facial behavior analysis toolkit**, T. Baltrušaitis et al., 2016]

Articulated Body Tracking: OpenPose

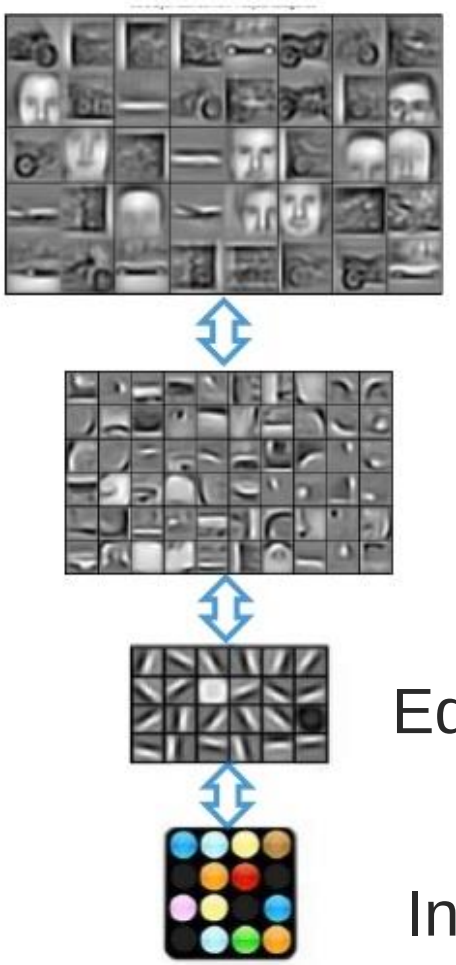
https://github.com/CMU-Perceptual-Computing-Lab/openpose

- See appendix for list of available tools for automatic visual behavior analysis

Convolutional Neural Networks

Why using Convolutional Neural Networks?

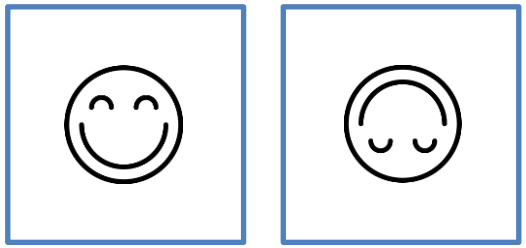
Goal: building more abstract, hierarchical visual representations



Key advantages:

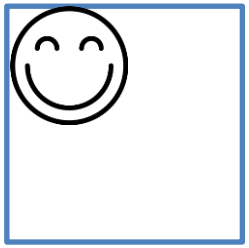
1) Inspired from visual cortex
2) Encourages visual abstraction
3) Exploits *translation invariance*
4) Kernels/templates are learned
5) Fewer parameters than MLP

Translation Invariance



2 Data Points – Which one is up?

- MLP can easily learn this task (possibly with only 1 neuron!)



What happens if the face is slightly translated?

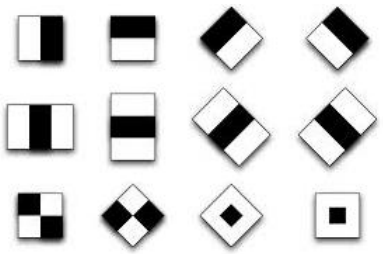
- The model should still be able to classify it

Conventional MLP models are not translation invariant!

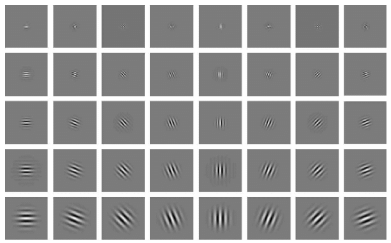
- But CNNs are kernel-based, which helps with translation invariance and reduce number of parameters

Learned vs Predefined Kernels

Predefined kernels



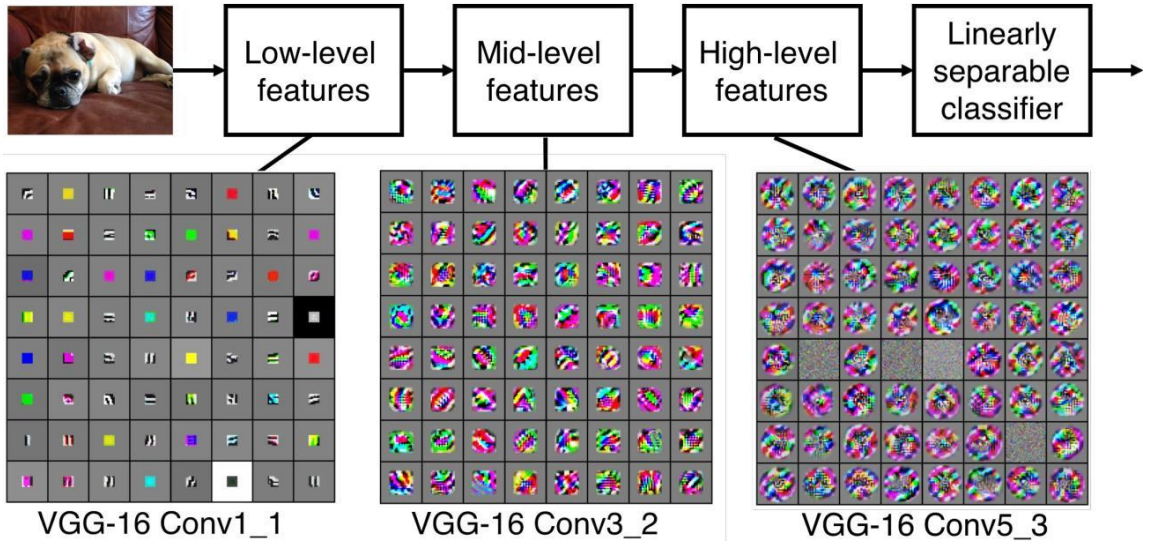
Haar Wavelets



Gabor filters

Learned kernels

Convolutional Neural Network (CNN)



With CNNs, the kernel values are learned as model parameters

Convolution

Convolution: Mathematical Definition

A basic mathematical operation (that given two functions returns a function)

$$(f * g)[n] \stackrel{\text{def}}{=} \sum_{m=-\infty}^{\infty} f[m]g[n-m]$$

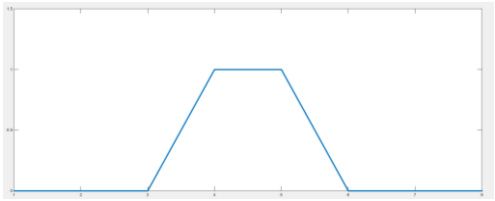
Two versions: continuous and discrete

(we will focus on the latter)

Convolution in 1D – Example

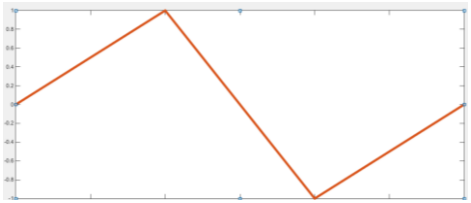
Input:

$$f = [\dots, 0,1,1,1,0,0, \dots]$$



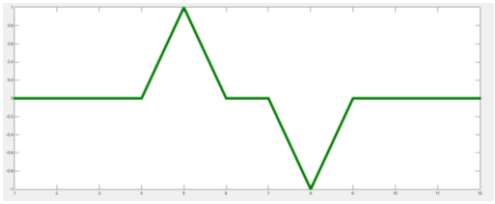
Kernel:

$$g = [\dots, 0,1,-1,0 \dots]$$



Convolution:

$$f * g = [\dots, 0,1,0,0,-1,0,0, \dots]$$



$$(f * g)[n] \stackrel{\text{def}}{=} \sum_{m=-\infty}^{\infty} f[m]g[n-m]$$

Convolution in practice

In CNN we only consider functions with limited domain (not from $-\infty$ to ∞)

CNN considers fully defined (valid) version:

- We have a signal of length N
- Kernel of length K
- Output will be length $\mathrm{N} - \mathrm{K} + 1$

Example: $f = [1,2,1]$, $g = [1,-1]$, $f * g = [1,-1]$

Convolution in practice

If we want output to be different sizes, we can add padding to the signal:

- Just add 0s at the beginning and end

$$f = [0,0,1,2,1,0,0],\ g = [1,-1],\ f * g = [0,1,1,-1,-1,0]$$

We can perform *strided (aka, dilated)* convolution: the filter jumps over pixels or samples

- Example with stride 2:

$$f = [0,0,1,2,1,0,0],\ g = [1,-1],\ f * g = [0,1,-1,0]$$

When would it be a good idea?

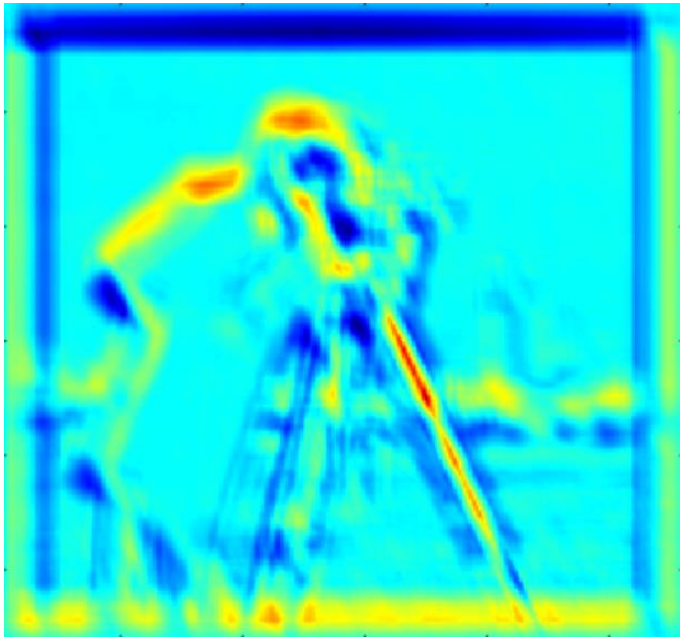
Convolution in 2D – Example

Input image

*

Convolution kernel

=

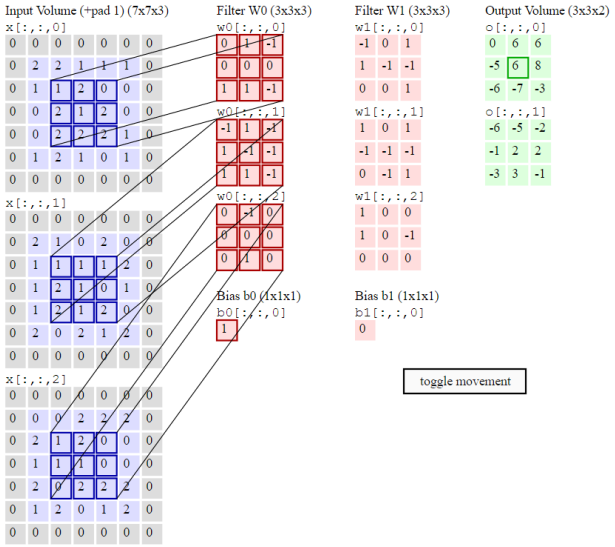


Response map

Sample CNN convolution

Great animated visualization of 2D convolution:

http://cs231n.github.io/convolutional-networks/



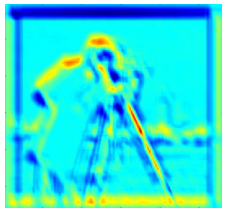
Convolutional Neural Layer

Convolution as a Fully-Connected Network

Input

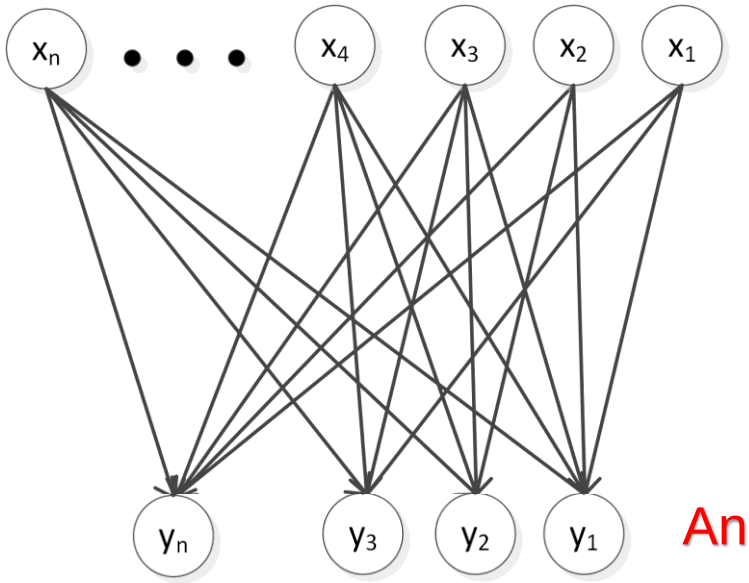
(image)

Output



(response map)

Input: all pixels



Output: kernel responses

Not efficient!

200×200 image
requires
$40{,}000 \times n$ parameters

(where n is size of kernel)

And it may learn different kernels for different pixel positions

➡ Not translation invariant

Convolutional Neural Layer

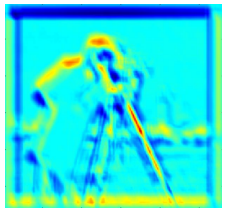
Input

(image)

Weighted sum

$\boldsymbol{Wx}$

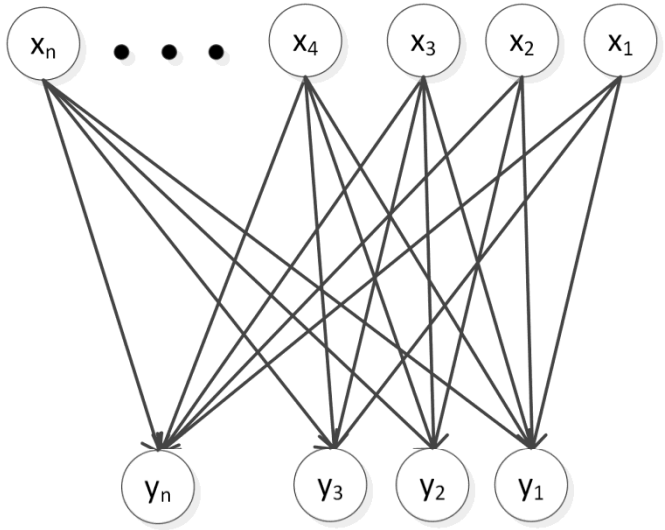
Output



(response map)

$y = Wx$

Input: all pixels



Output: kernel responses

Example with 1D kernel:

w_1	w_2	w_3

Convolutional Neural Layer

Modification 1: Remove redundant links making the matrix W sparse

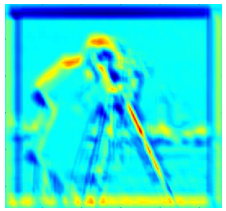
Input

(image)

Weighted sum

Wx

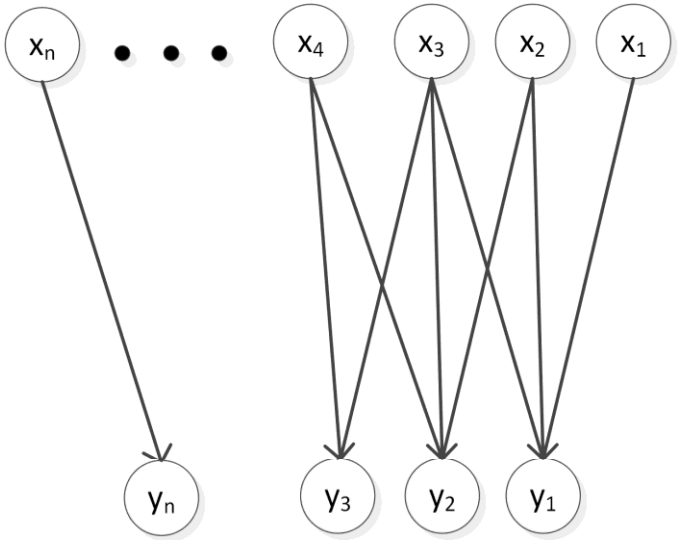
Output



(response map)

$y = Wx$

Input: all pixels



Output: kernel responses

Example with 1D kernel:

w_1	w_2	w_3

Convolutional Neural Layer

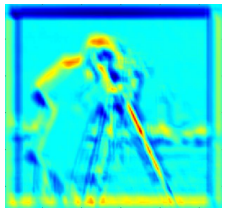
Modification 2: share the weights in matrix W
not to do redundant computation

Input

(image)

Weighted sum
Wx

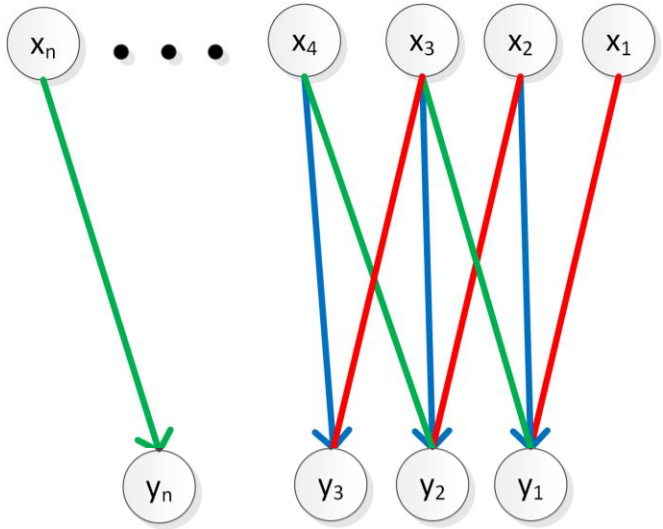
Output



(response map)

$y = Wx$

Input: all pixels



Output: kernel responses

Example with
1D kernel:

Convolutional Neural Layer

Modification 2: share the weights in matrix W
not to do redundant computation

Input

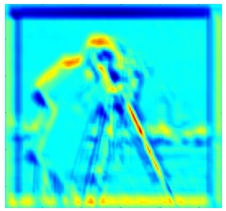
(image)

$$W = \begin{pmatrix} w_1 & w_2 & w_3 & & & 0 & 0 & 0 \\ 0 & w_1 & w_2 & \cdots & & 0 & 0 & 0 \\ 0 & 0 & w_1 & & & 0 & 0 & 0 \\ & \vdots & & \ddots & & & \vdots & \\ 0 & 0 & 0 & & w_3 & 0 & 0 & \\ 0 & 0 & 0 & \cdots & w_2 & w_3 & 0 & \\ 0 & 0 & 0 & & w_1 & w_2 & w_3 & \end{pmatrix}$$

Example with 1D kernel:

w_1	w_2	w_3

Output



(response map)

$$y = Wx$$

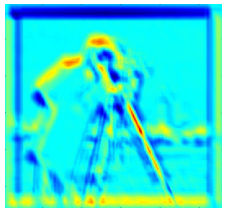
Can be implemented efficiently on GPUs

Convolutional Neural Layer

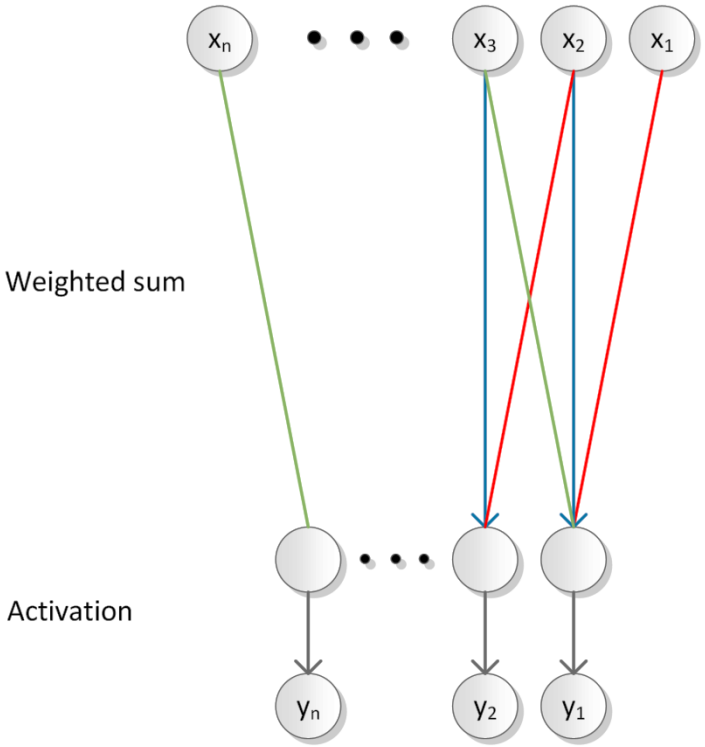
Input

(image)

Output



(response map)



Example with 1D kernel:

w_1	w_2	w_3

$$y = \sigma(Wx + b)$$ with the activation function, and bias terms

Convolutional Neural Layer

Can expand this to 2D (or even 3D!)

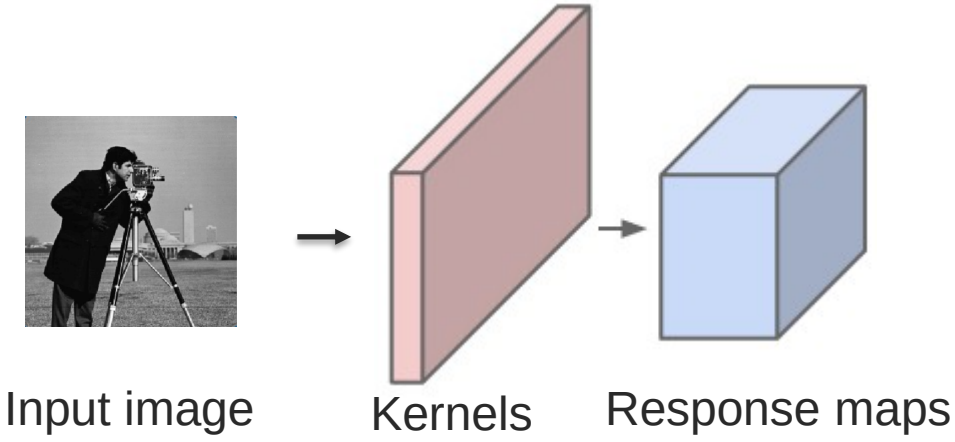
- Just need to make sure to link the right pixel with the right weight

Can expand to multi-channel 2D

- e.g., for RGB images

Can expand to multiple kernels/filters

- Output is not a single image anymore, but a tensor (a 3D matrix)



Convolutional Neural Network

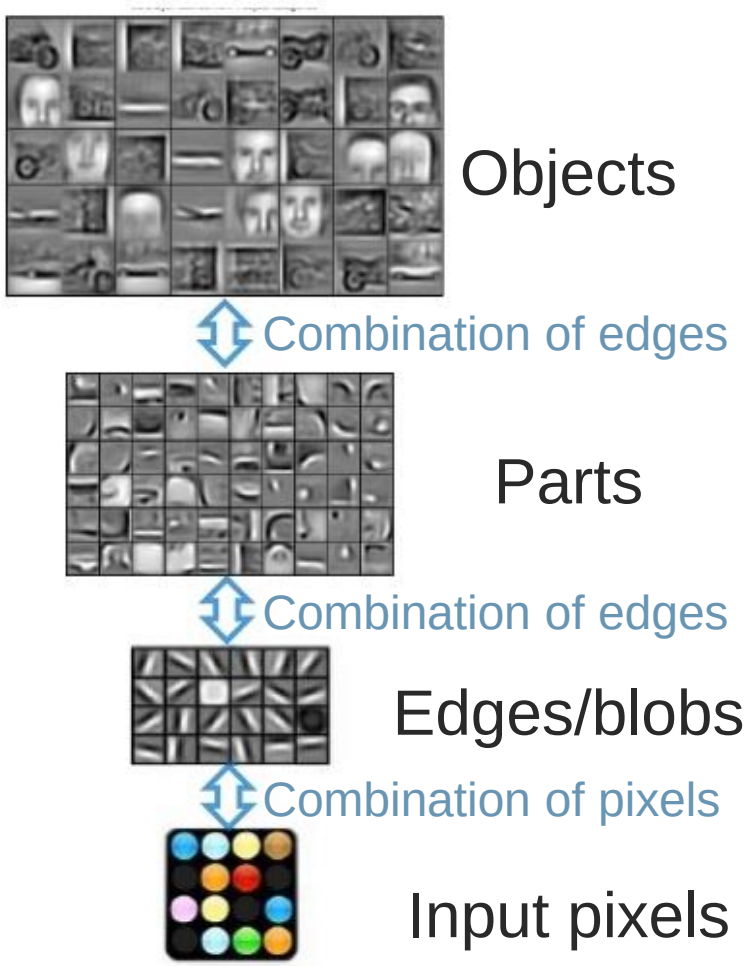
Convolutional Neural Network

Multiple convolutional layers

- Allows the network to learn combinations of sub-parts, to increase complexity

but how to encourage abstraction and summarization?

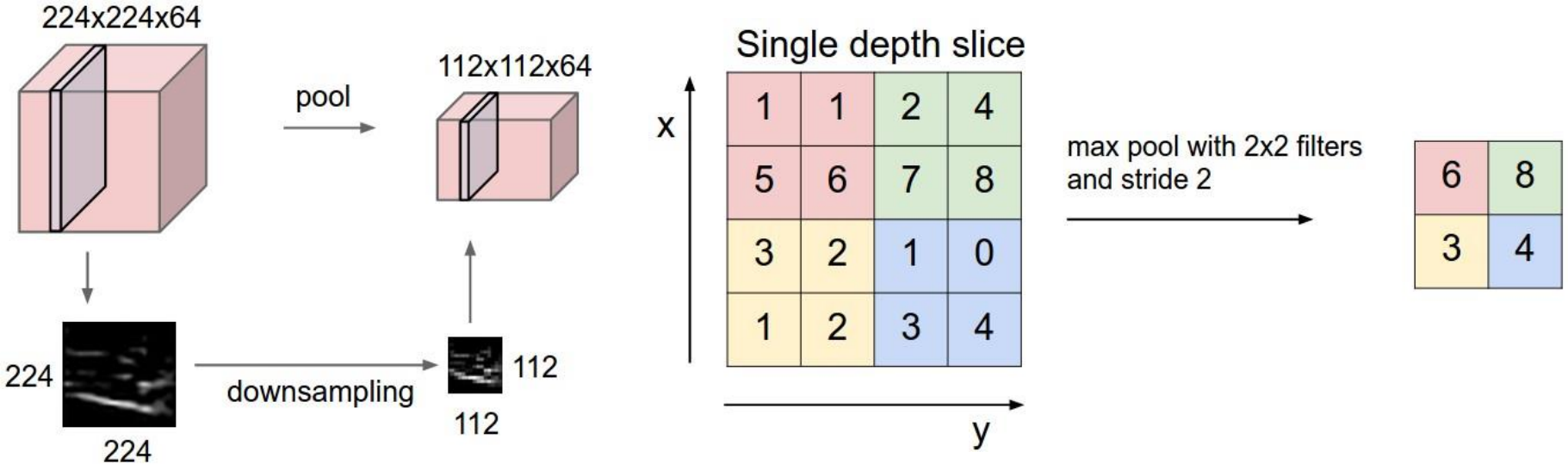
Answer: Pooling layers



Pooling Layer

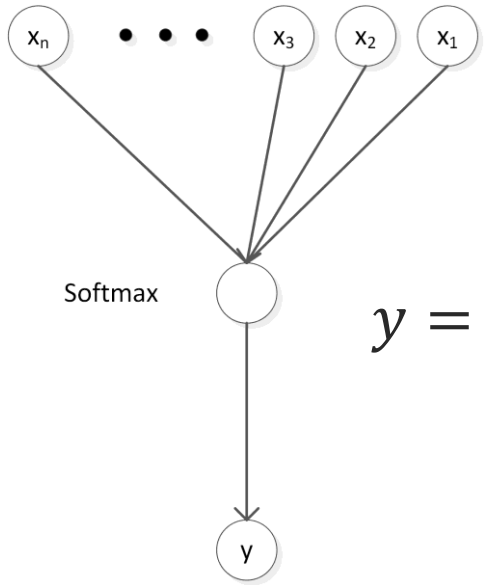
Response map subsampling:

Allows summarization of the responses



Pooling Layer Gradient

1. Record during forward pass which pixel was picked and use the same in backward pass
2. Pick the maximum value from input using a smooth and differentiable approximation



$$y = \frac{\sum_{i=1}^{n} x_i e^{\alpha x_i}}{\sum_{i=1}^{n} e^{\alpha x_i}}$$

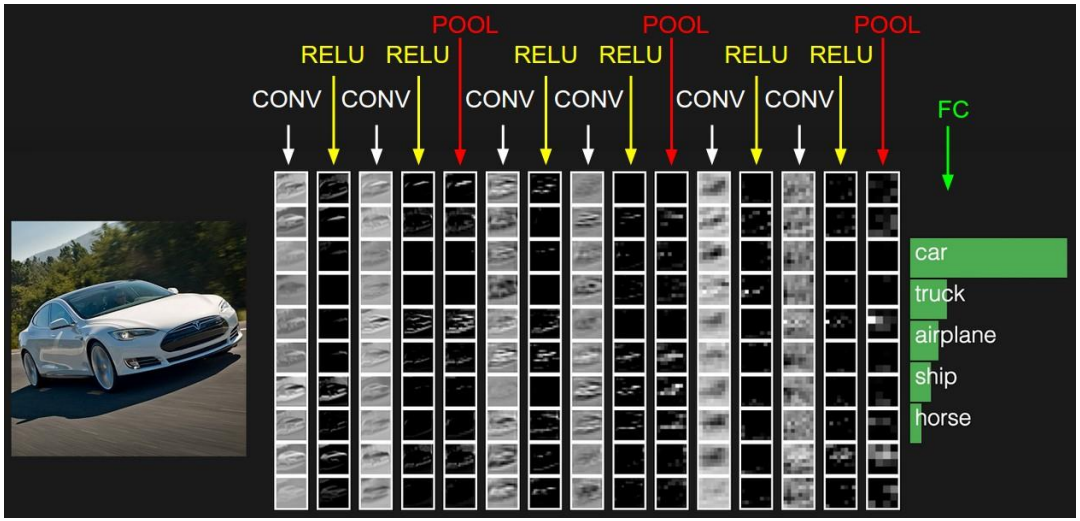
Example of CNN Architectures

Common architectures

Start with a convolutional layer follow by non-linear activation and pooling

Repeat this several times

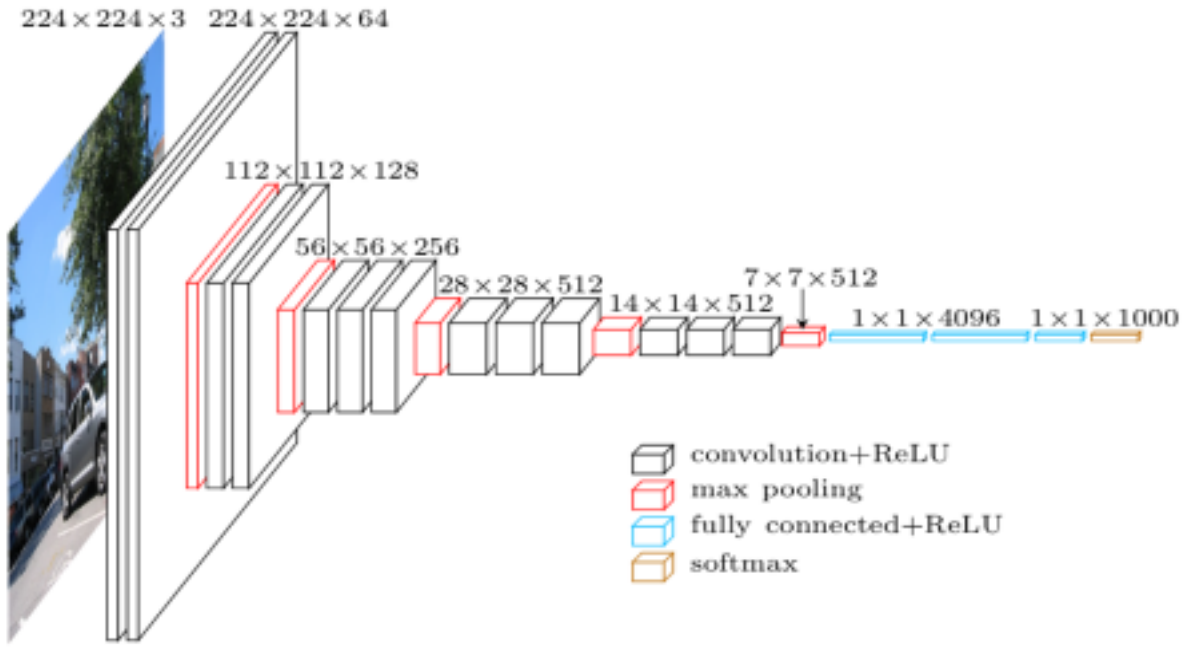
Ends with a fully connected (MLP) layer



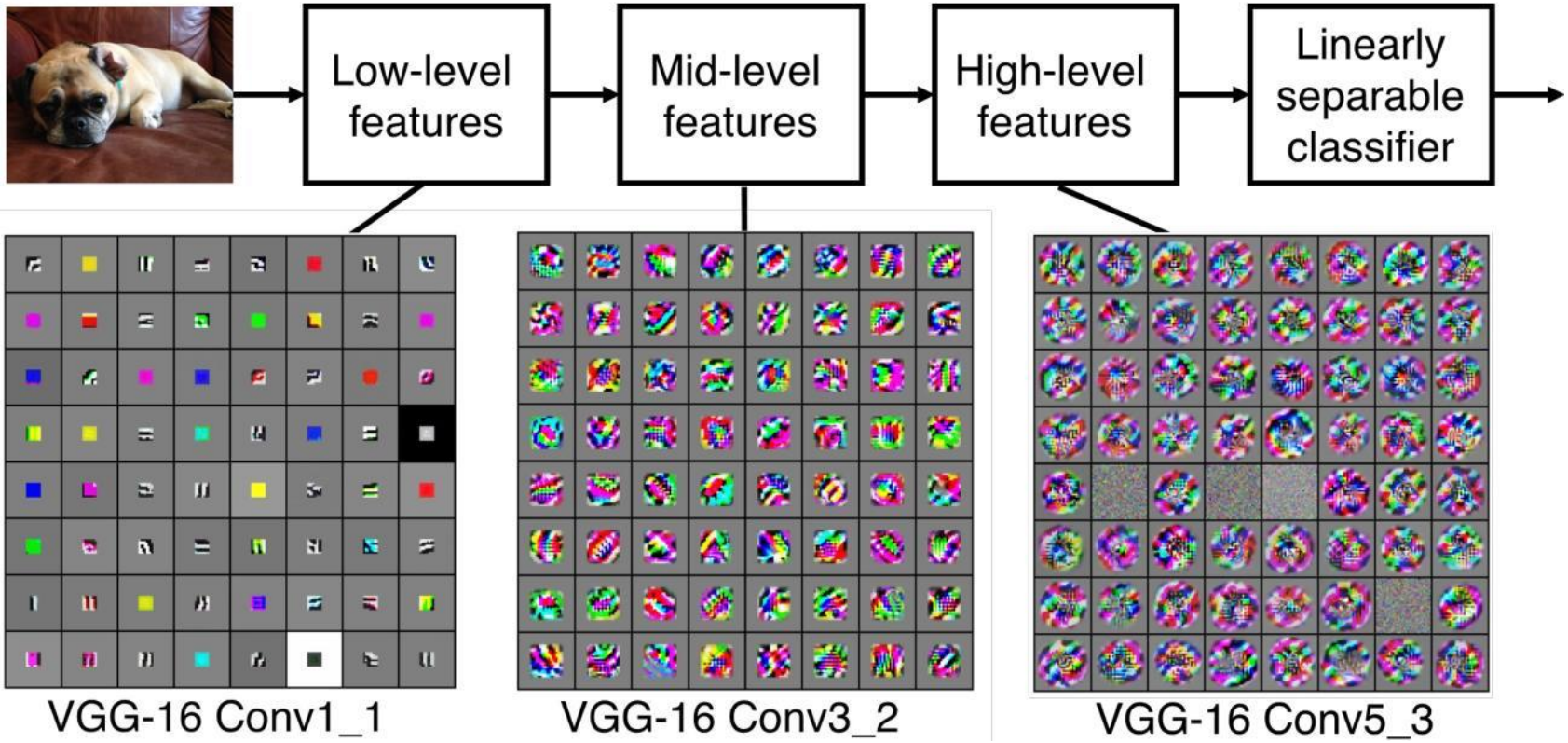
VGGNet model

Used for object classification task

- 1000-way classification task
- 138 million parameters

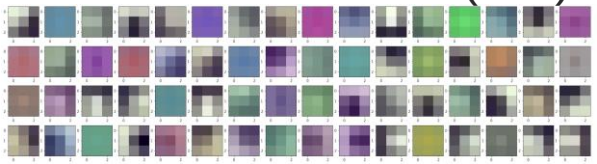


VGGNet Convolution Kernels

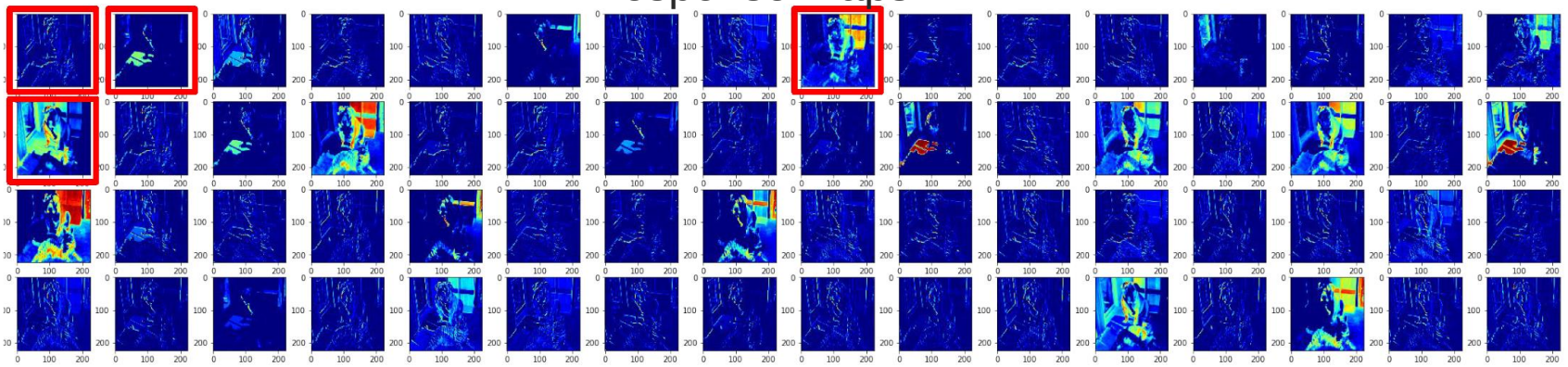


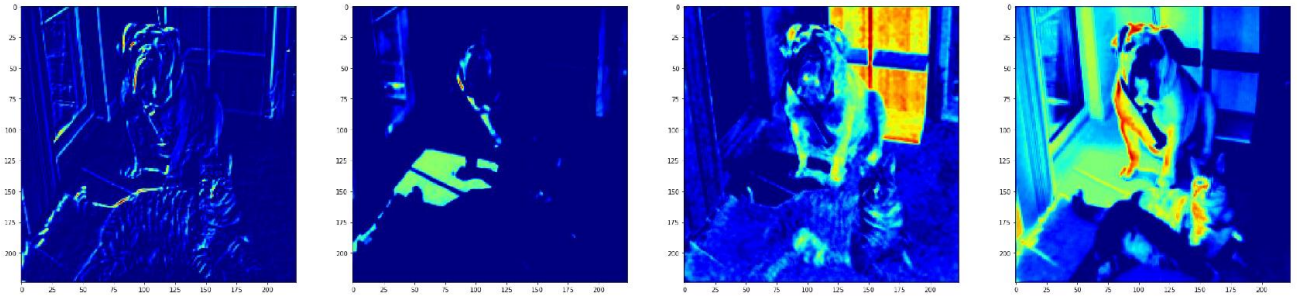
VGGNet Response Maps (aka Activation Maps)

Convolution kernels (3x3)



Response Maps





Other architectures

LeNet – an early 5 layer architecture for handwritten digit recognition

DeepFace – Facebook's face recognition CNN

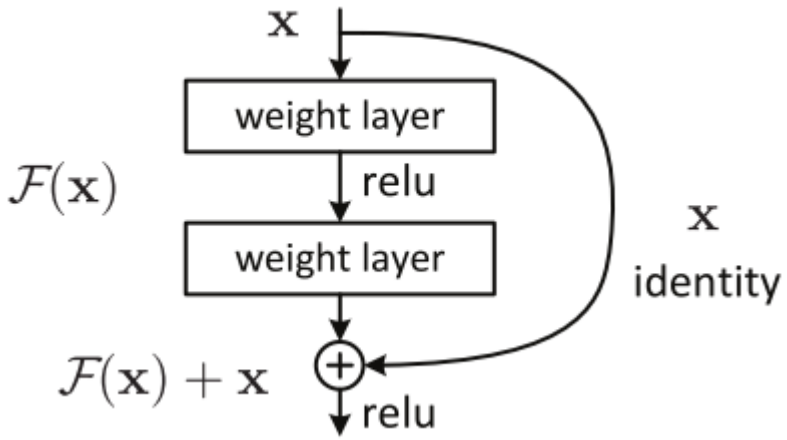
VGGFace – For face recognition (from VGG folks)

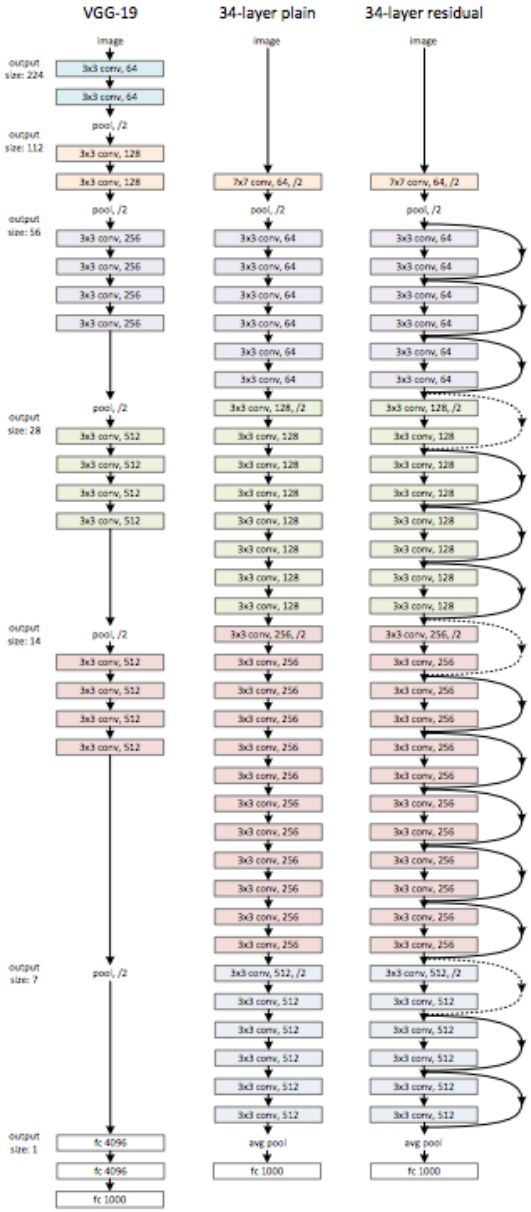
AlexNet – Object Recognition

Already trained models for object recognition can be found online

Residual Networks

Adding residual connections





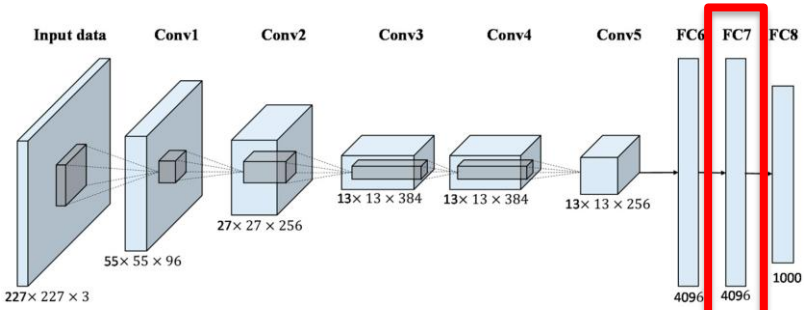
ResNet (He et al., 2015)

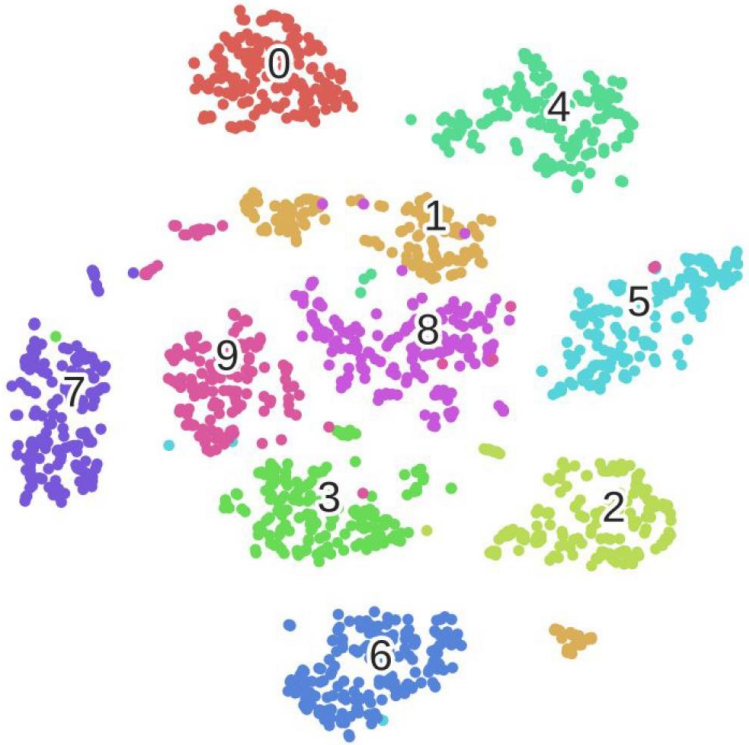
- Up to 152 layers!

Visualizing CNNs

Visualizing the Last CNN Layer: t-sne

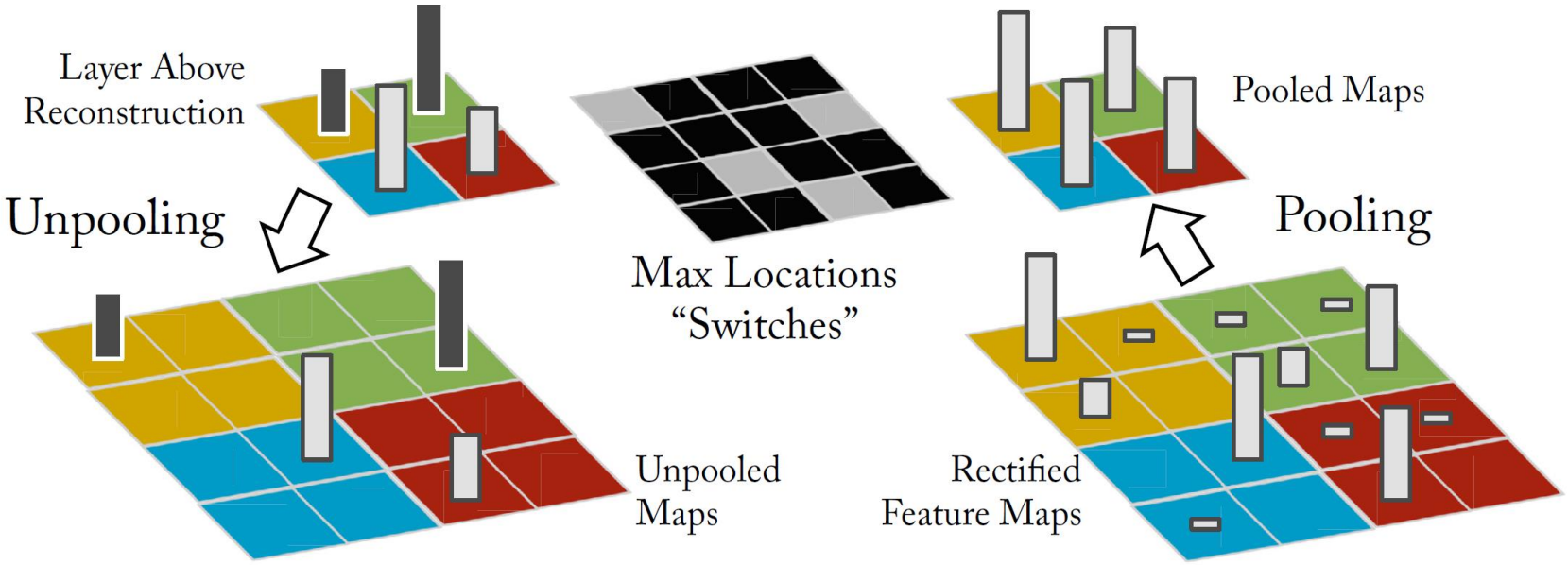
Alex Net



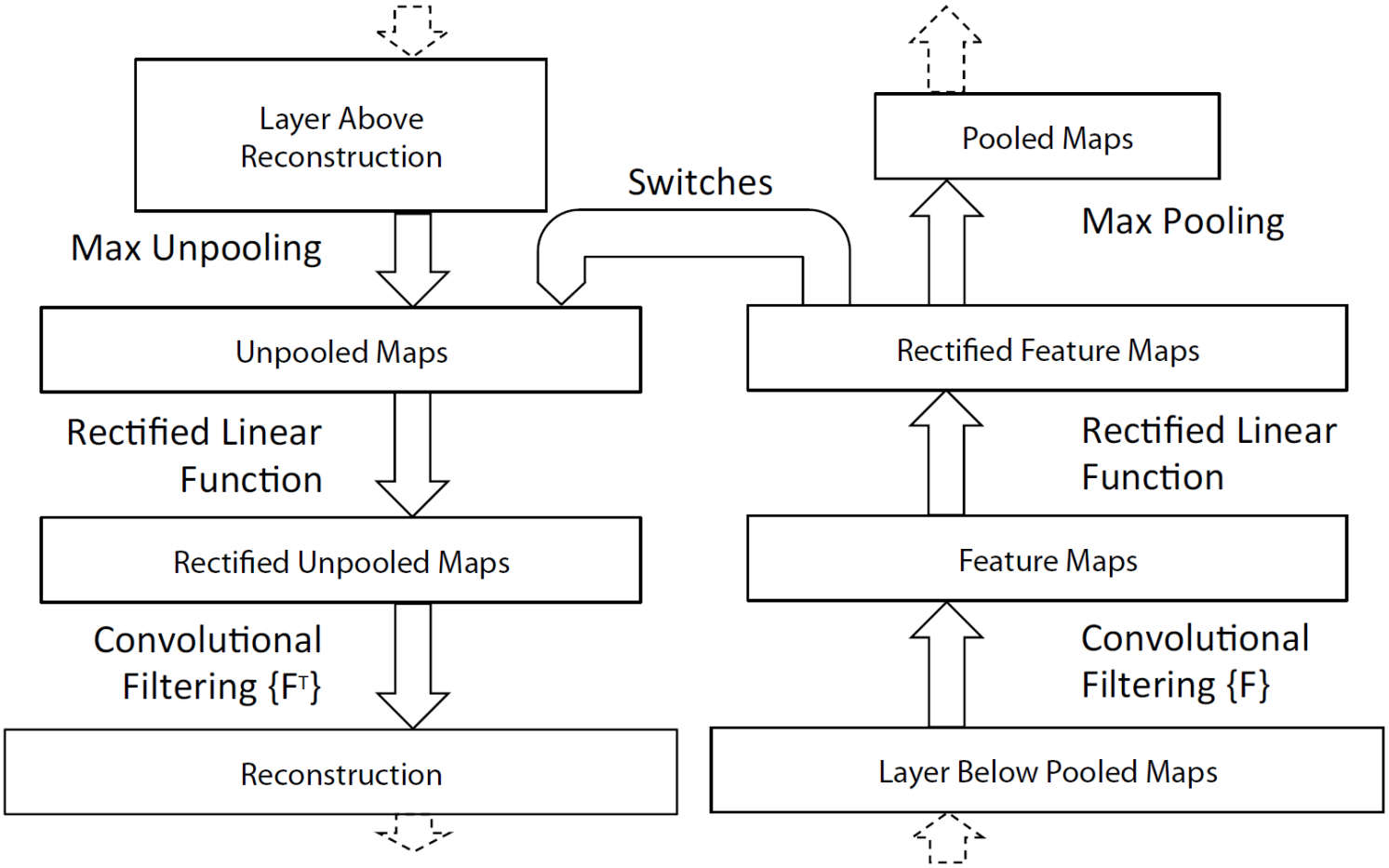


Embed high dimensional data points (i.e. feature codes) so that pairwise distances are conserved in local neighborhoods.

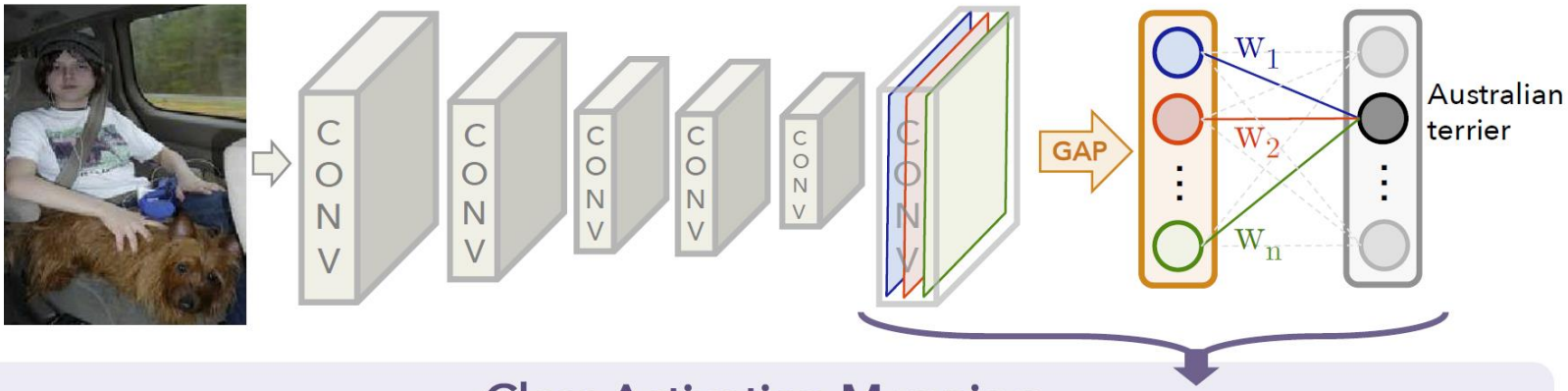
Deconvolution



Deconvolution

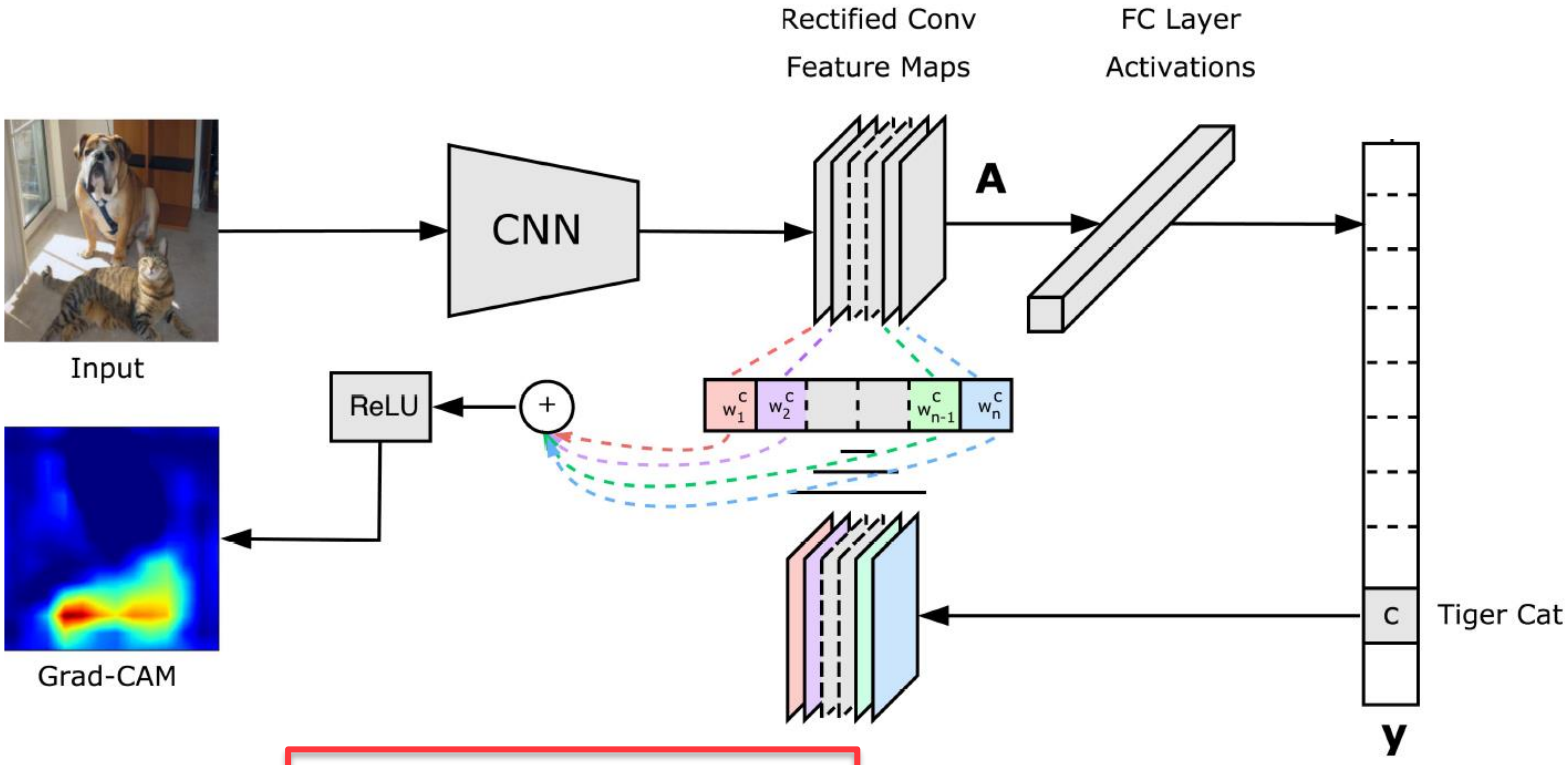


CAM: Class Activation Mapping [CVPR 2016]



$$L^c_{\text{CAM}} = \underbrace{\sum_k w^c_k A^k}_{\text{linear combination}}$$

Grad-CAM [ICCV 2017]



$$\alpha_k^c = \overbrace{\frac{1}{Z}\sum_i\sum_j}^{\text{global average pooling}} \underbrace{\frac{\partial y^c}{\partial A_{ij}^k}}_{\text{gradients via backprop}}$$

$$L^c_{\text{Grad-CAM}} = ReLU\underbrace{\left(\sum_k \alpha_k^c A^k\right)}_{\text{linear combination}}$$

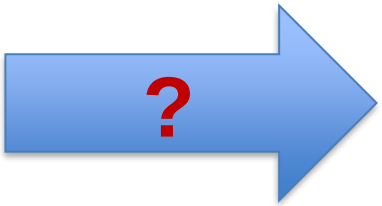
Region-based CNNs

Object recognition

Input Image

Object Detection (and Segmentation)

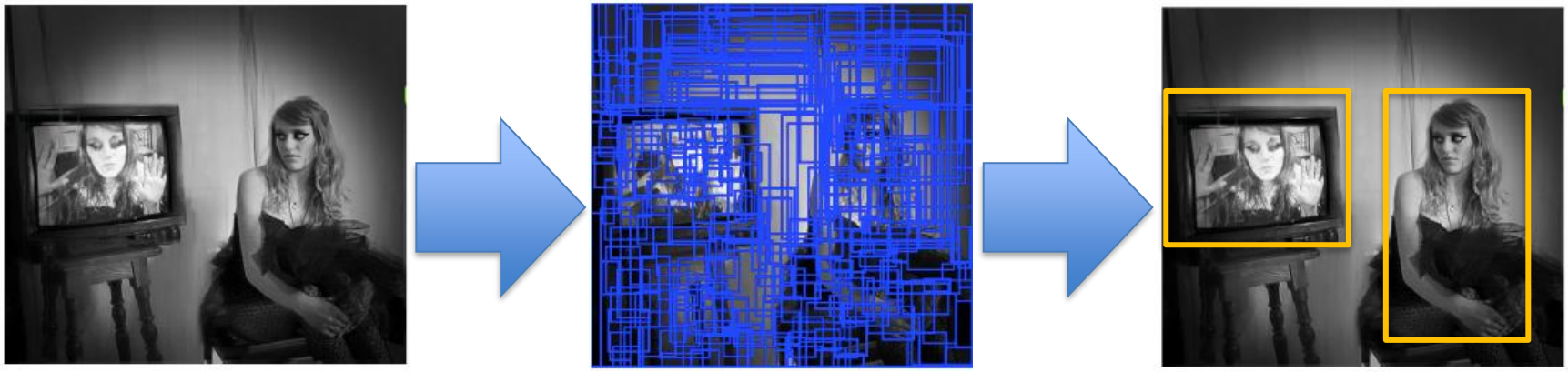
Input image



Detected Objects

One option: Sliding window

Object Detection (and Segmentation)



Input image | Region Proposals | Detected Objects

A better option: Start by Identifying hundreds of region proposals and then apply our CNN object detector

How to efficiently identify region proposals?

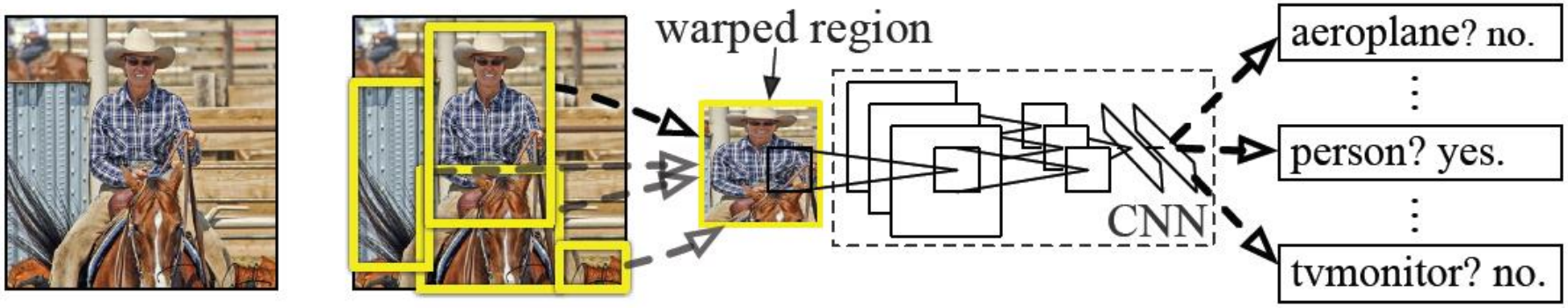
Selective Search [Uijlings et al., IJCV 2013]

Image segmentation
(using *superpixels*)

And then merge
similar regions

Create box
region proposals

R-CNN [Girshick et al., CVPR 2014]

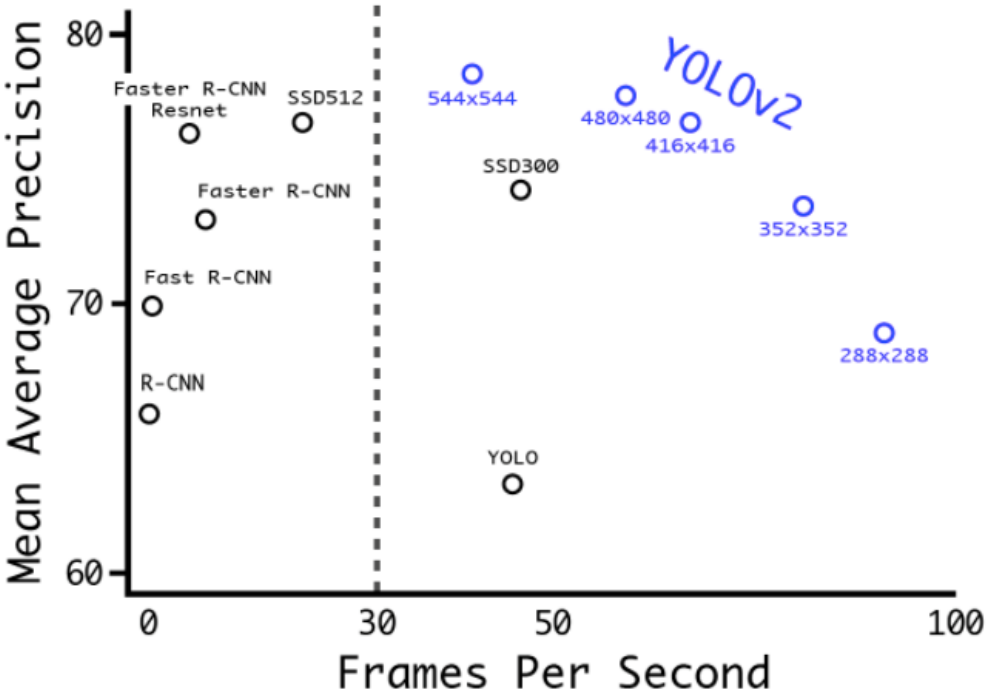


- Select ~2000 region proposals → Time consuming!
- Warp each region
- Apply CNN to each region → Time consuming!

Fast R-CNN: Applies CNN only once, and then extracts regions

Faster R-CNN: Region selection on the Conv5 response map

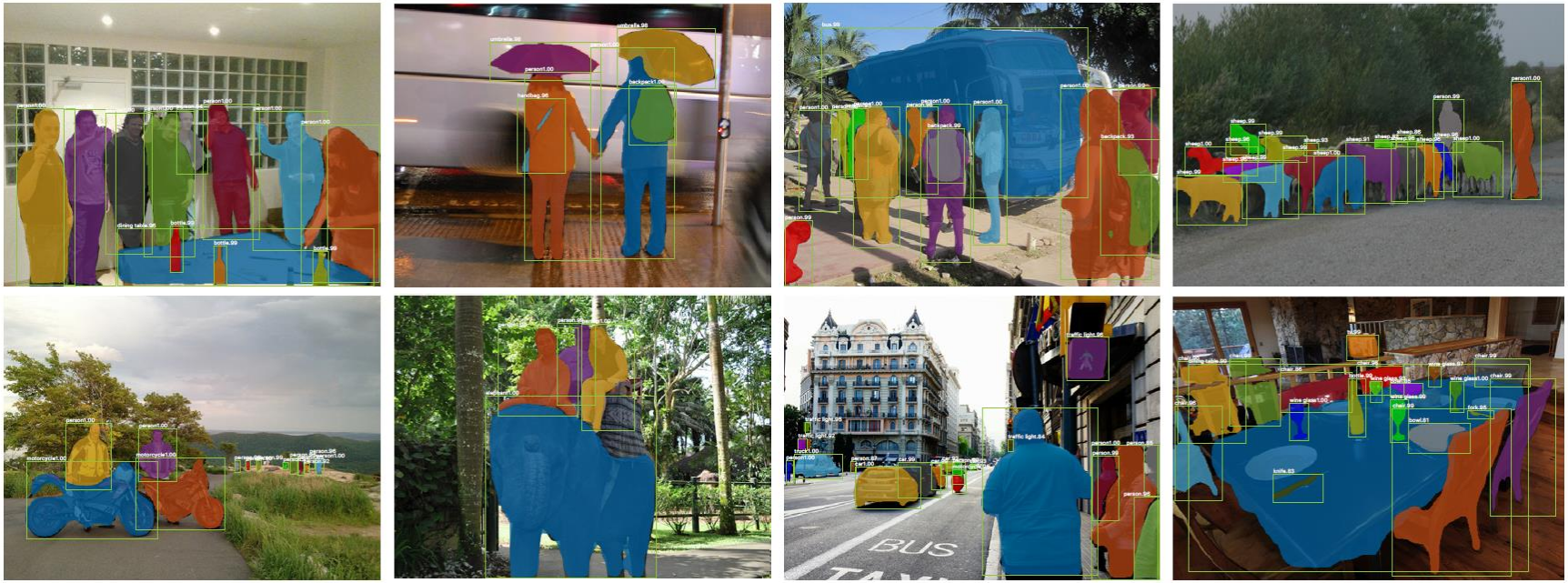
Trade-off Between Speed and Accuracy



YOLO: You Only Look Once (CVPR 2016, 2017)
SSD: Single Shot MultiBox Detector (ECCV 2016)

Mask R-CNN: Detection and Segmentation

(He et al., 2018)



Sequential Modeling with Convolutional Networks

Modeling Temporal and Sequential Data

How to represent a video sequence?

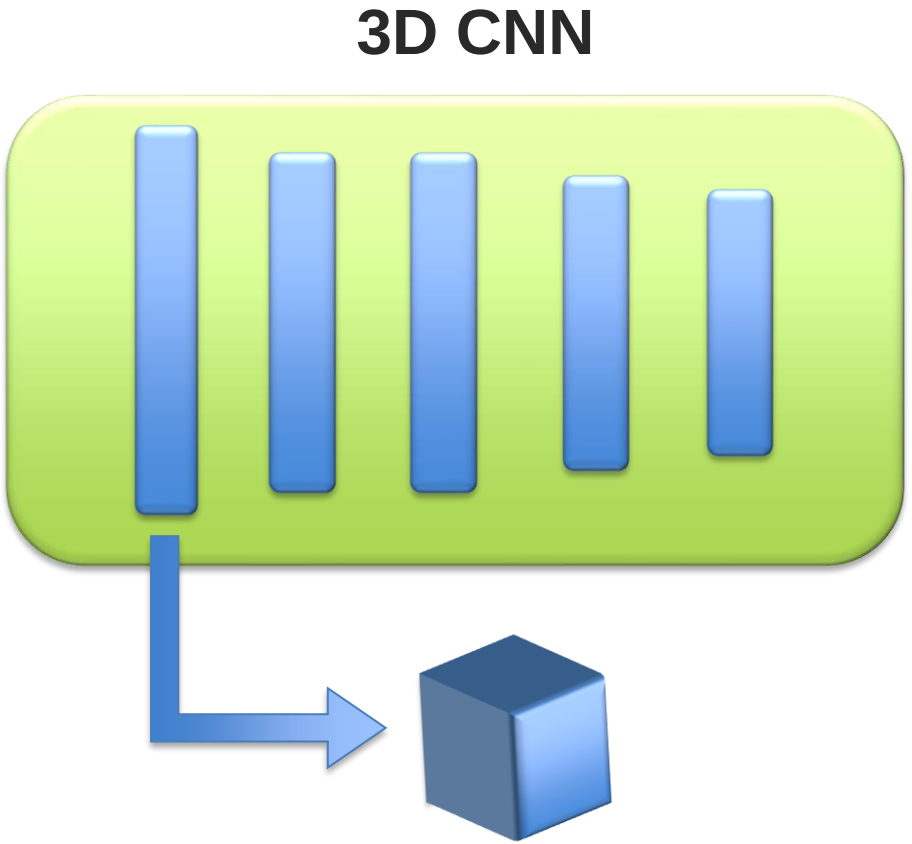
One option: Recurrent Neural Networks

(more about this on Thursday)

3D CNN

Input as a 3D tensor

(stacking video images)

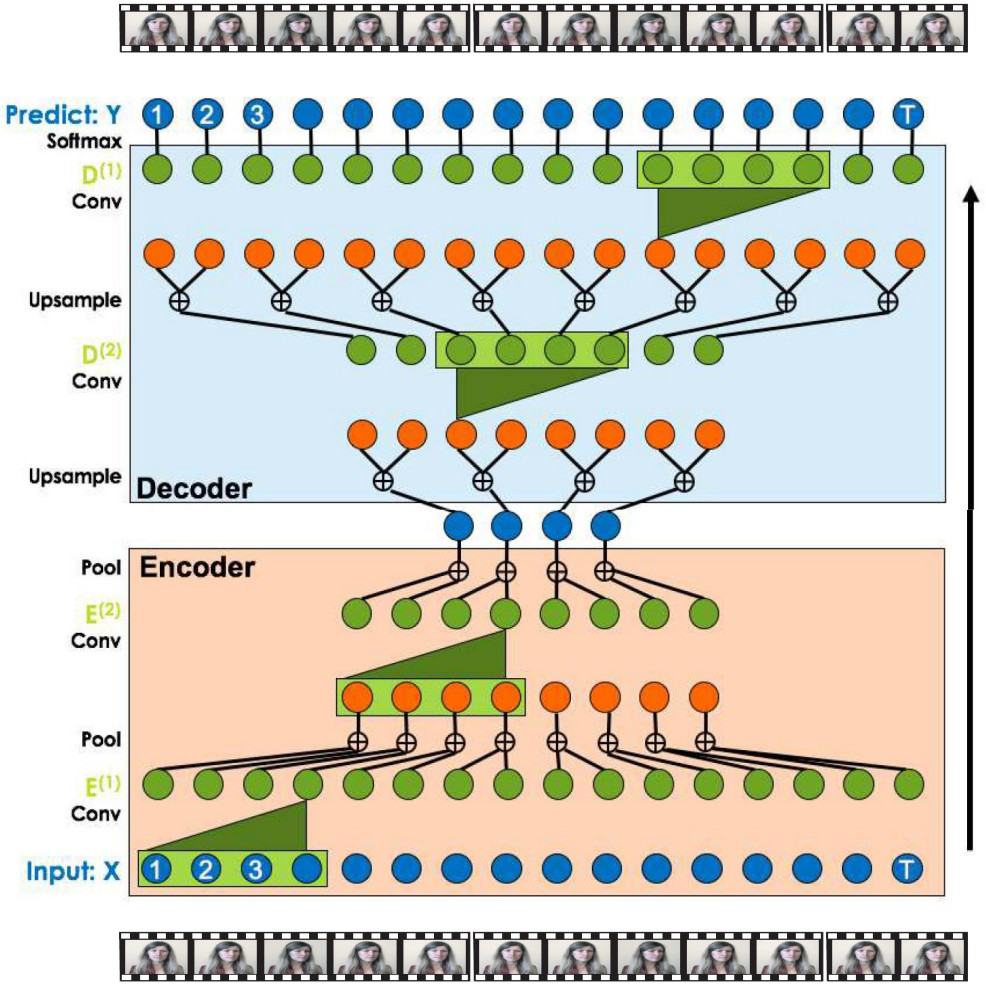


First layer with 3D kernels

Time-Delay Neural Network

Alexander Waibel, Phoneme Recognition Using Time-Delay Neural Networks, SP87-100, Meeting of the Institute of Electrical, Information and Communication Engineers (IEICE), December, 1987,Tokyo, Japan.

Temporal Convolution Network (TCN) [Lea et al., CVPR 2017]

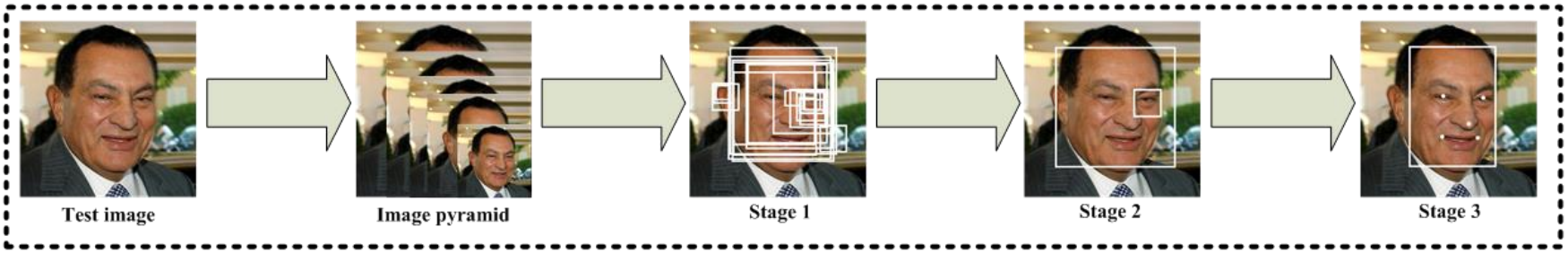


Appendix: Tools for Automatic visual behavior analysis

Automatic analysis of visual behavior

- Face detection
- Face tracking
  - Facial landmark detecion
- Head pose
- Eye gaze tracking
- Facial expression analysis
- Body pose tracking

Face Detection – Multi-Task CNN [SPL 2016]



Stage 1: candidate windows are produced through a fast Proposal Network

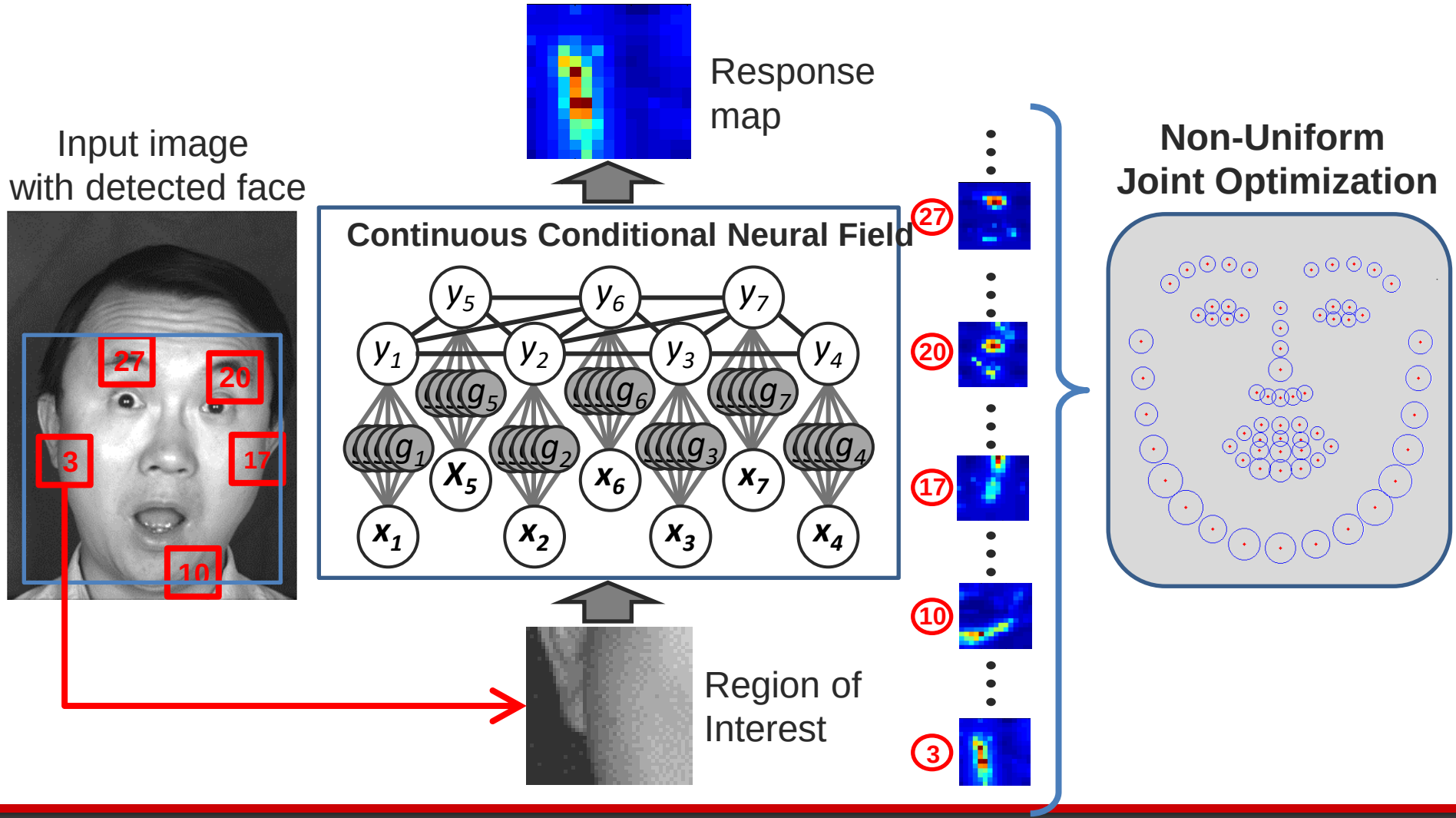
Stage 2: refine these candidates through a Refinement Network

Stage 3: produces final bounding box and facial landmarks position

Existing software (face detection)

- Multi-Task CNN face detector
  - https://kpzhang93.github.io/MTCNN_face_detection_alignment/index.html
- OpenCV (Viola-Jones detector)
- dlib (HOG + SVM)
  - http://dlib.net/
- Tree based model (accurate but very slow)
  - http://www.ics.uci.edu/~xzhu/face/
- HeadHunter (accurate but slow)
  - http://markusmathias.bitbucket.org/2014_eccv_face_detection/
- NPD
  - http://www.cbsr.ia.ac.cn/users/scliao/projects/npdface/

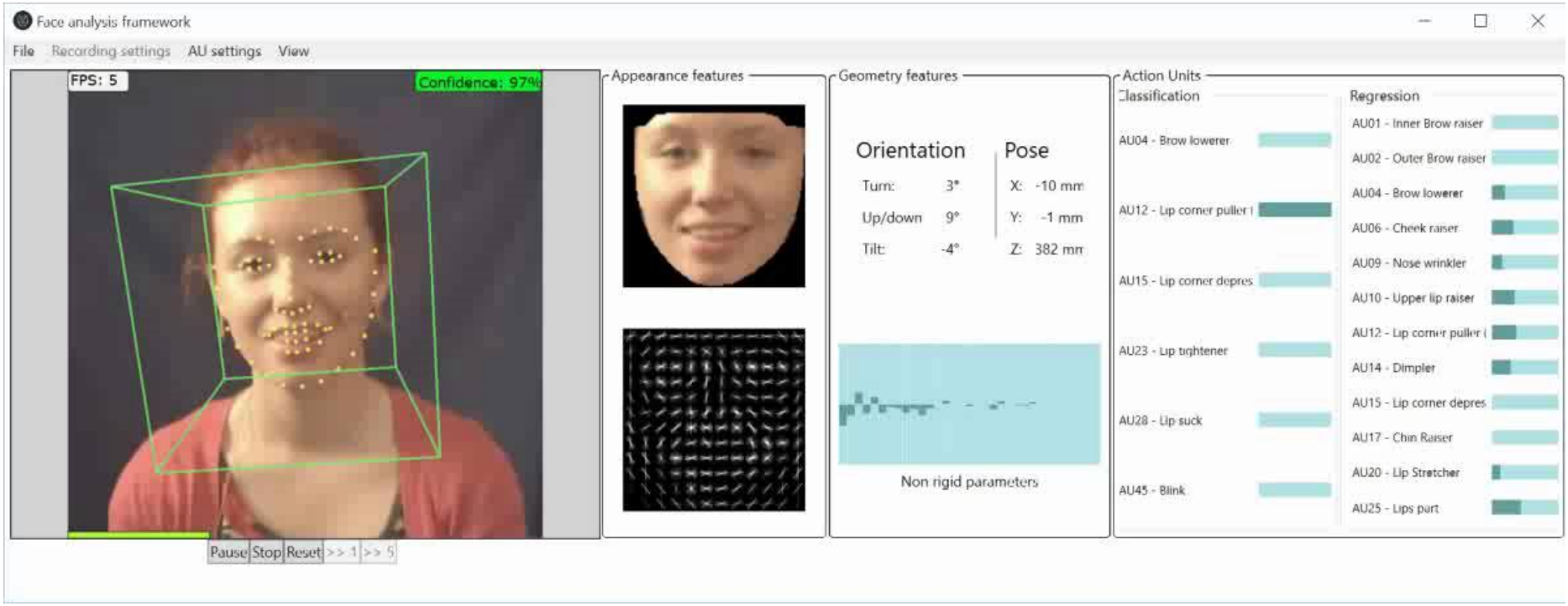
Facial Landmarks: Constrained Local Neural Field



Existing software (facial landmarks)

- OpenFace: facial features
  - https://github.com/TadasBaltrusaitis/OpenFace
- Chehra face tracking
  - https://sites.google.com/site/chehrahome/
- Menpo project (good AAM, CLM learning tool)
  - http://www.menpo.org/
- IntraFace: Facial attributes, facial expression analysis
  - http://www.humansensing.cs.cmu.edu/intraface/
- OKAO Vision: Gaze estimation, facial expression
  - http://www.omron.com/ecb/products/mobile/okao03.html (Commercial software)
- VisageSDK
  - http://www.visagetechnologies.com/products/visagesdk/
  - (Commercial software)

Facial expression analysis



[**OpenFace: an open source facial behavior analysis toolkit**, T. Baltrušaitis et al., 2016]

Existing Software (expression analysis)

- OpenFace: Action Units
  - https://github.com/TadasBaltrusaitis/OpenFace
- Shore: facial tracking, smile detection, age and gender detection
  - http://www.iis.fraunhofer.de/en/bf/bsy/fue/isyst/detektion/
- FACET/CERT (Emotient API): Facial expression recognition
  - http://imotionsglobal.com/software/add-on-modules/attention-tool-facet-module-facial-action-coding-system-facs/ (Commercial software)
- Affdex
  - http://www.affectiva.com/solutions/apis-sdks/
  - (commercial software)

Gaze Estimation – Eye, Head and Body

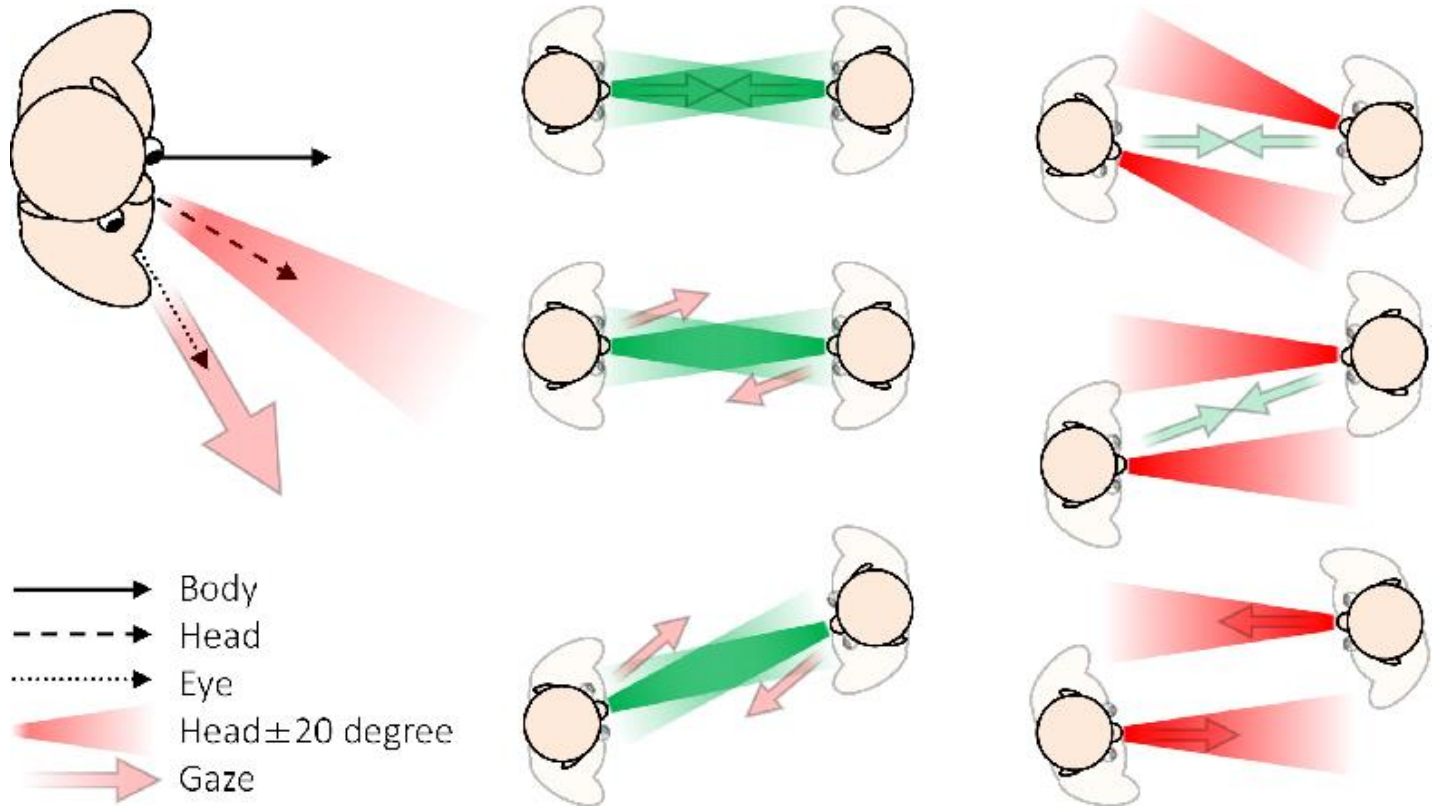
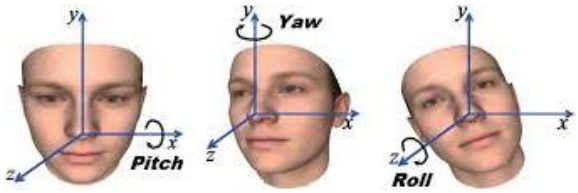


Image from Hachisu et al (2018). FaceLooks: A Smart Headband for Signaling Face-to-Face Behavior. *Sensors*.

Existing Software (head gaze)



- OpenFace
  - https://github.com/TadasBaltrusaitis/OpenFace
- Chehra face tracking
  - https://sites.google.com/site/chehrahome/
- Watson: head pose estimation
  - http://sourceforge.net/projects/watson/
- Random forests
  - http://www.vision.ee.ethz.ch/~gfanelli/head_pose/head_forest.html
  - (requires a Kinect)
- IntraFace
  - http://www.humansensing.cs.cmu.edu/intraface/

Existing Software (eye gaze)

- OpenFace: gaze from a webcam
  - https://github.com/TadasBaltrusaitis/OpenFace
- EyeAPI: eye pupil detection
  - http://staff.science.uva.nl/~rvalenti/
- EyeTab
  - https://www.cl.cam.ac.uk/research/rainbow/projects/eyetab/
- OKAO Vision: Gaze estimation, facial expression
  - http://www.omron.com/ecb/products/mobile/okao03.html (Commercial software)

Articulated Body Tracking: OpenPose

Existing Software (body tracking)

- OpenPose
  - https://github.com/CMU-Perceptual-Computing-Lab/openpose
- Microsoft Kinect
  - http://www.microsoft.com/en-us/kinectforwindows/
- OpenNI
  - http://openni.org/
- Convolutional Pose Machines
  - https://github.com/shihenw/convolutional-pose-machines-release

Visual Descriptors

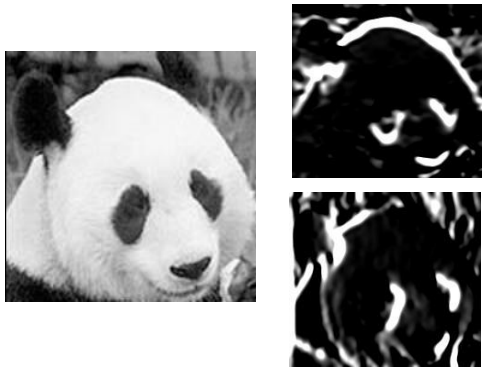
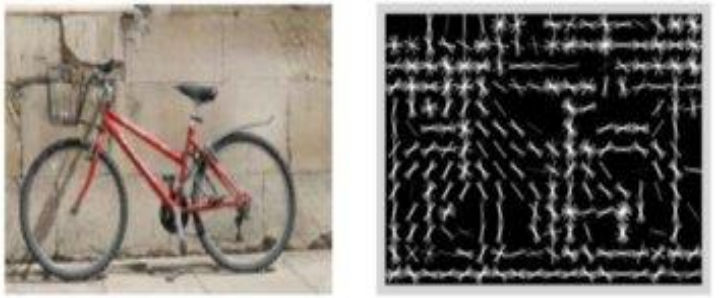


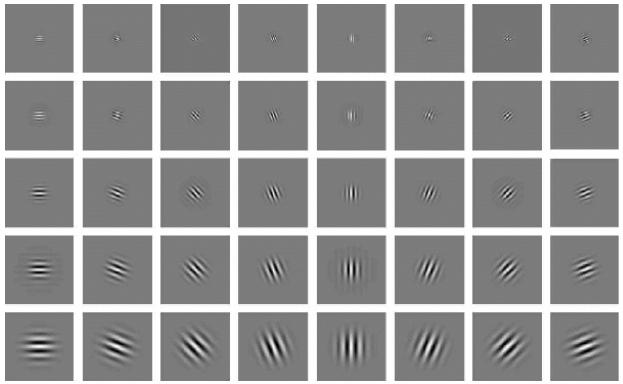
Image gradient

Edge detection

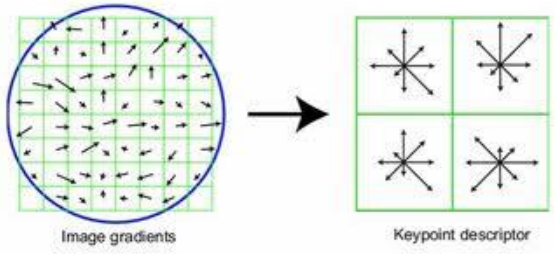


Histograms of Oriented Gradients

Optical Flow



Gabor Jets



SIFT descriptors

Existing Software (visual descriptors)

- OpenCV: optical flow, gradient, Haar filters…
- SIFT descriptors
  - http://blogs.oregonstate.edu/hess/code/sift/
- dlib – HoG
  - http://dlib.net/
- OpenFace: Aligned HoG for faces
  - https://github.com/TadasBaltrusaitis/CLM-framework